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Ruiz Conde, Maria del Enar

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Maria del Enar Ruiz Conde

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Modeling Innovation Diffusion Patterns

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Maria del Enar Ruiz Conde

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Promotor

Prof. dr. P.S.H. Leeflang

Copromotor

Dr. J.E. Wieringa

Beoordelingscommissie

Prof. dr. T.H.A. Bijmolt
Prof. dr. F.J. Mas Ruiz
Prof. dr. D.R. Wittink

To Joaquín.

Preface

In this thesis I invested several years of my life. Although I like to start new adventures, when I started this one I did not have a clear idea of the road to follow but, step by step, I found the way that led me to a fulfilling end. Many people have been involved in this adventure which, like any other, has had exciting but also critical moments. I would like to share my feelings with and express my gratitude to these people.

When the Department of Financial Economics, Accounting and Marketing of the Faculty of Economics of the University of Alicante offered me the opportunity to join them, I did not imagine that my professional, but also personal, life would experience the changes and take the direction that it finally has taken. I would like to thank the department director, Juan Carlos Gomez Sala, and also the dean of the faculty, Joaquín Marhuenda Fructuoso, for their continued interest in the progress of this research and for supporting me by providing the necessary means for its completion.

Guided by the suggestions of the various department directors over these years and in order to contribute to the development of my thesis, I have divided my time between teaching marketing and attending several courses and seminars over and above my doctoral courses in Alicante. It was during a doctoral course that Peter S.H. Leeflang appeared in my life. To be precise, we first met in April 2001 when I was attending an interesting and useful course on marketing modeling, organized by the European Institute for Advanced Studies in Management (EIASM), in Brussels. In October of that year, he came to the University of Alicante and it was then that he started supervising my thesis. I would like to express my profound thanks for his wise supervision, his valuable suggestions and constructive criticism that have enabled me to finish this work. It has been an honor to have had Peter as my promotor and I feel very fortunate to have had this opportunity.

I first met Jaap Wieringa in January 2002, in a seminar I was presenting on my first trip to Groningen (a very exciting experience). However, I started to work with him over a year later, March 2003 to be exact. From the beginning, working with Jaap has been a pleasure. We have spent many hours working together, both on-line and face to face. I am very grateful to him for sharing his knowledge with me, for establishing valuable discussions and for providing appropriate suggestions, which together have made an invaluable contribution to this work.

I do not have enough space to properly thank my promotor, Peter S.H. Leeflang, and co-promotor, Jaap Wieringa, for their contribution to my professional development, through this thesis, and also to my personal life. They have always made me feel one of their close group and have made my visits to Groningen as comfortable as possible. When you are working abroad, far from your family and friends, finding people that make you to feel at home is a real blessing. Peter and his wife, Hanneke, and Jaap and his wife, Nathalie, have been these people for me.

Thank you sincerely for the opportunity of working with you and also for the moments we have spent together. I am also grateful to the rest of the Department of Marketing of the Faculty of Economics of the University of Groningen for their warm and welcoming approach. I am especially grateful to Liane Voerman for agreeing to be my “paranimf” and for giving me her cheerful help and support.

I would like to greatly acknowledge the reading committee, Professors Tammo Bijmolt, Francisco Mas Ruiz and Dick Wittink, for their willingness to read the manuscript, and for their useful comments and suggestions for improvements.

I am thankful for the friendly working relationship I have with my departmental colleagues in the University of Alicante, which has facilitated my research and has provided me with a comfortable working environment. I am also thankful to Cristina Gironés Ansuátegui and Juan España Valor for always being available when I needed them. Also thanks to Gillian Stark and Tim Curtis for correcting my English. I am especially thankful to my colleagues David Abad Díaz and Belen Nieto Domenech, who joined the department on exactly the same day as I and have always been close to me and have supported me at all times. I would like to thank Pepa Parreño Selva (my Spanish “paranimf”) and Aurora Calderón Mártinez for their never-ending support; they are not only fantastic colleagues but are also wonderful friends who have shared very exciting moments with me and have helped me through certain difficult moments in the development and finishing of this thesis.

I am grateful to Francisco Mas Ruiz, not only for his suggestions for the development of this work, but also for his thrust in me and for the professional and personal backing he has given.

Finally, I would like to dedicate some special words to my family and friends. “*Gracias a mis amigos por los ánimos que me han transmitido en todo momento y por la paciencia que han tenido durante todos estos años. Gracias a mi familia por estar siempre ahí. A mis suegros, Mari Carmen y Joaquín por haber sido tan maravillosos conmigo y haberme aceptado como una hija más. A mis tíos, Felo y Dora, Arturo y Regina, y a mi primo Enrique, que siempre han estado presentes y dispuestos para mí. A mis entrañables, queridos y admirados Papas Annes, Ángel y Ángeles, que siempre han estado, están y estarán a mi lado con sus sabias y dulces palabras. A mis padres, Mariví y Manolo, que cuando me encuentro perdida siempre me hacen ver una salida, que cuando me encuentro triste siempre me animan, que cuando no están presentes siempre los llevo dentro.*

Y a tí, Joaquín, qué puedo decir que tu no sepas ya; has sido la clave para finalizar esta tesis, tu apoyo, tu cariño, tu sonrisa, …tu presencia me han dado las fuerzas para embarcarme en esta aventura y concluirla. Te quiero.”

Alicante, October 2004
Enar Ruiz Conde

Contents

Chapter 1

Introduction

The understanding of the diffusion process of new products is a key factor in the strategic planning of a company and, as such, justifies the amount of contributions from different fields, such as Industrial Economics, Strategic Management and Marketing. In fact, the diffusion process can well prevail over the innovation itself, since its economic and social impact is generated by adopters of the innovation, and hence it becomes an important stimulus for new innovations. Interest in the performance of innovations in the marketplace has generated many studies in an attempt to design a model of the spread of an innovation at the aggregated level over time (Mahajan and Muller, 1979).

The diffusion of an innovation is defined as the process through which the innovation "*is communicated through certain channels over time among the members of a social system*" (Rogers, 1983, p.5). Although diffusion is directly or indirectly affected by many different factors (such as the type of innovation, communication channels, either inter-personal and/or mass-media, the type of social system and time), the notion of diffusion is essentially a form of communication. That is, diffusion has to be considered as the propagation of messages related to new ideas that lead to subsequent innovations (products, processes, technology, etc.), with an expectation of change in receptor behavior, which will be evident in the adoption or the rejection of the innovation. Firms know that new products shape their future. Consumer-products firms churned out 31,000 new products in 2000 (Kotler, 2003). However, new products fail at a disturbing rate. Mahajan, Muller and Wind (2000) point out that the failure rates of new products are between 40 and 90%. Therefore, managers are interested in understanding the sales growth of innovations introduced in the market as well as the aspects that affect it. This implies understanding the diffusion process of innovations.

The underlying behavioral theory suggests that a time-lag exists during the adoption period among the different members of a social system. In the first stage of the diffusion process, the new product is discovered and adopted by a small group of innovative consumers, known as innovators who, with time, begin to influence others, known as imitators. This social interaction between adopting pioneers and potential adopters explains the phase of rapid expansion in the diffusion process (Rogers, 1983). Taking into account this underlying innovation behavior, most researchers have tried to model the diffusion process of innovations through mathematical expressions; specifically, they have found an important area of knowledge around innovation diffusion models. Since firms are continually introducing new products in the marketplace and given the complexity and risk inherent in decisions on innovation management, diffusion models can be useful tools for managers to reduce the risk inherent in the introduction of an innovation.

Diffusion models in marketing have a main representative, the Bass (1969) model. Although the Bass model has a large acceptance in the literature on the diffusion of innovations, the assumptions on which this model is based limit its applicability. Researchers interested in the diffusion of innovations try to relax these limitations through modifications of the model. Furthermore, although the Bass model was intended for consumer durable innovations and the majority of its applications are on this kind of innovation, several researchers are demonstrating its applicability to other innovations (such as frequently purchased consumer products or services). However, more research is needed in that direction to consolidate the Bass model and its extensions as useful tools to understand the diffusion processes of different kinds of innovations in different settings.

1.1. Contribution of this research

The aim of our research is to contribute to the methodological and substantive evolution of diffusion models toward a better understanding of their application potential. In particular, we consolidate the convenience of using diffusion models to understand the diffusion process of any innovation (consumer products, services, organizational innovations, etc.), and extend diffusion models to accommodate effects that are not present in many of the existing models (such as marketing variables or repeat purchases).

Although most diffusion studies concentrate on new durable consumer products (such as blenders, calculators, clothes dryers, dishwashers, freezers, irons, microwave ovens or color and black and white TVs), we need to increase our knowledge on other innovation types. The enlargement of the traditional applications (consumer durables) of the diffusion models in marketing (especially Bass-type models) usually implies the relaxation of some of the mentioned restrictive assumptions through an extended diffusion model that accounts for specific details. The managers involved in the introduction of new products in the markets are interested in both useful tools to help them to reduce the uncertainty inherent in innovation decisions and useful information on the performance of similar innovations in similar situations or contexts. The useful tools are the diffusion models extended to account for specific details and the useful information comes from the findings of research on different innovations in different markets or countries.

In this thesis we present applications in which we propose several specifications for diffusion models that relax some of the restrictive assumptions on which the classical models are based. The proposed extensions reduce the rigidity of this model type and bring them closer to reality. Specifically, we address three empirical applications where extended diffusion models are analyzed and innovations other than durable consumer products are considered. In the first application we focus on movies, which are entertainment and experience consumer products. In the second application, we study the diffusion of an organizational innovation, namely franchising. Finally, in the third application, we study the diffusion of several brands of prescription drugs, which are frequently purchased consumer products.

1.2. Study outline

Chapter 2, *Diffusion of innovations: Theoretical considerations*, is dedicated to theoretical issues concerning the diffusion of innovations. We present the origins of research on diffusion modeling, the value of the diffusion models in both the academic and business context. We introduce the market segments commonly considered in the diffusion process of innovations, the mathematical specification of a diffusion model and the terminology that is used in the remainder of this thesis. The last section of the chapter is dedicated to the assumptions -limitations- of the classical diffusion models. We review and discuss the body of research of diffusion models that relax these assumptions.

Chapter 3, *An introduction to three empirical applications*, outlines the empirical analyses developed in this thesis and specifies their characteristics regarding the type of innovation, the decision maker, the assumptions relaxed through the extended diffusion models and the country analyzed. In this short chapter we justify why we propose several extended diffusion models and their applications on the three studies presented in each of the following chapters.

In Chapter 4, *Diffusion of movies in neighboring Mediterranean countries*, we extend the Bass model by accommodating for distribution. This extension is especially relevant since this marketing decision variable is rarely incorporated and hence more research on the influence of this variable in the diffusion models is needed. Furthermore, this extension is also convenient, especially for the product analyzed, given that previous research on movies finds that distribution (i.e. the number of screens on which a movie is released) is the most important influence on viewership among other factors (such as movie attributes such as genre or presence/absence of starts). We use diffusion models to analyze differences in the diffusion process of movies in several countries that are geographically close. Differences in revealed preferences and differences in the moment of entry in these countries are investigated. The understanding of the diffusion process of a new product in a specific geographical area (region or country) is obviously relevant and has clear implications to managers when planning the introduction of the new product (or another movie with similar characteristics) in another geographical area.

In Chapter 5, *Diffusion of franchising in Spain*, we analyze the diffusion process of an organizational innovation, namely franchising. This analysis presents a double interest for both managers and researchers. Firstly, there are no previous studies that analyze the diffusion of franchising among firms as an organizational innovation from the point of view of the franchisors (i.e. inter-firm diffusion). The extraordinary expansion of this managerial organization system has created thousands of jobs and has generated a turnover of millions of euros, which indicates the importance of franchising for managers and, in general, for the countries. Secondly, the use of the classical diffusion models to understand the diffusion process of organizational innovations that starts in the early 80's with the studies of Teece (1980) and Thompson (1983) on the multidivisional form structure and that of Antonelli (1985) on International Data Telecommunications, suffers a set back when Mahajan, Sharma and Bettis (1988) question the imitation hypothesis behind the classical diffusion models, for organizational innovations. Our study shows the suitability of the imitation hypothesis in the diffusion of franchising as an organizational innovation.

In Chapter 6, *Diffusion of prescription drugs in the United States of America*, we use diffusion modeling to investigate longitudinal and cross-sectional effects of marketing expenditures on the diffusion of new pharmaceuticals. The pharmaceutical industry is the most profitable industry in the USA for each of the ten years before 2002. The pharmaceutical industry spends billions of dollars on marketing. Diffusion models can be valuable tools to help managers to analyze the role of pharma marketing in the introduction of new drugs in the market. Hence, the classical diffusion models are not appropriate in this setting. We look for a diffusion model that differentiates between the trial and repeat rates of the new drugs and that also explicitly accounts for marketing variables.

Finally, in Chapter 7, *Summary and discussion*, we provide a summary of the results of this thesis. We present the conclusions and contributions of the thesis and discuss limitations and directions for future research.

Chapter 2

Diffusion of innovations: Theoretical considerations

In this chapter we first discuss the origins of research into diffusion models and emphasize the value of these models in marketing. We then present the mathematical structure of a diffusion model and, finally, we discuss the assumptions of traditional diffusion models. Most of this chapter is dedicated to evaluating the body of research on diffusion modeling and discussing models that relax the limitations of the classical diffusion models (i.e. extended models or advanced models). Although there are studies that review diffusion models of innovations in marketing, such as those by Mahajan and Muller (1979), Mahajan, Muller and Bass (1990, 1993), Parker (1994) and Mahajan, Muller and Wind (2000), our review provides additional useful information and new research. We consider relevant research on the relaxation of the assumption of traditional diffusion models and we show the main contributions and the contexts in which the authors apply the proposed models. We specifically:

- indicate how authors introduce the extensions in the models specifying whether they extend the external, the internal or the mixed influence formulation;
- show the mathematical specification that the authors use to extend the classical diffusion models; and
- specify the number of assumptions relaxed by each of the reviewed studies and present them in a summary table (see Appendix 2B, Table 2B). This shows the level of relaxation applied by each study.

Furthermore, the terminology used by other authors is adapted to that used in this thesis, in order to facilitate comparison among the models (summary tables are provided).

We pay special attention to the assumptions addressed in the following chapters, although all the assumptions of the classical diffusion models are reviewed and discussed in the thesis.

In our study we focus on solving some of the restrictive assumptions behind the classical diffusion models and show, through empirical analyses, how relaxing these assumptions offers opportunities to better understand the diffusion process of innovations.

2.1. Origins of research on diffusion models

Despite the fact that diffusion is essentially a form of communication based on the spread of new ideas, research on the diffusion of innovations does not directly emerge from communication research. As Rogers[1] (1976) points out, there are multiple diffusion origins. One origin is the British and German-Austrian schools of diffusion in anthropology. The members of these schools held that most changes in a society are the result of the introductions of innovations by other societies. Another source is the French sociologist Tarde (1903). He proposed the S-shaped diffusion curve and emphasized the role of opinion leaders in the "imitation" process.

Research on diffusion reaches a decisive moment in the early 60's, when the diffusion field starts to emerge as an individual body of knowledge with its own concepts and generalizations (Rogers, 1971)[2].

In the early 60's, the diffusion concept also receives special attention in marketing. The interest from the business world stimulates research into diffusion by the academic world. Firms competing in the marketplace are aware of the huge failure indexes in the launch of a new product[3]. This motivates them to find a tool to help them face one of the most risky decisions; that of developing and introducing new products into the marketplace.

The amount of work developed in recent decades emphasizes the considerable attention that researchers have paid to the diffusion of innovations[4]. Insofar as diffusion is a process that cuts across the changes that a social system experiences (Sharif and Ramanathan, 1982) and, in particular, individual behavior, it is logical that the diffusion process is considered a key element of study in many disciplines. Hence, research on diffusion has its theoretical and empirical roots in a great number of disciplines such as anthropology (Linton, 1936; Childe, 1937; Barnett, 1953; Steward, 1963), sociology (Tarde, 1903; Bowers, 1937; Rogers, 1962; Katz, Levin and Hamilton, 1963), medical sociology (Coleman, Katz and Menzel, 1957, 1966), education (Mort, 1964; Carlson, 1968), geography (Hägerstrand, 1967; Brown, 1968), politics (Walker, 1969; Gray, 1972), industrial economy (Mansfield,

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1 Rogers (1976) refers to Katz (1960) and Rogers (1967) in an in-depth study into the convergence between research on diffusion and research on communication.

2 Rogers (1976) points out that this does not necessarily mean that every researcher in diffusion agrees completely on the most appropriate definitions or research methods, but at least they recognize that they are researching the same form of human behavior.

3 Conner (1964) estimates that only 8% of approximately 6000 new consumer products introduced in the market each year have a life expectancy of at least one year. Crawford (1977) and Mahajan, Muller and Wind (2000) points out that the failure rates of new products are between 40 and 90%. Rasmussen, (1998) finds a failure percentage of new products of 80%.

4 The diffusion process is perhaps the most researched and best documented social phenomenon (Rogers, 1983).

1961), communication (Lazarsfeld, Berelson and Gaudet, 1948; Rogers and Shoemaker, 1971) and marketing (King, 1966; Bass, 1969; Robertson, 1971).

Although these interests are diverse, each area of research has contributed, in some way, to diffusion theory. Sociologists and geographers have paid attention to the spatial[5] issues of the diffusion processes and to the socioeconomic factors that affect such processes. Researchers in marketing, industry and technology have focused on the temporal pattern of an innovation when this penetrates a population. Haynes, Mahajan and White (1977) and Mahajan and Peterson (1979) have used both points of view.

2.2. Value of diffusion models

Diffusion models in marketing describe the diffusion process of an innovation in a society over time (Rogers, 1983). Diffusion models concern the spread of an innovation, from its launch to the innovation being adopted by successive individuals within a social system. Thus, diffusion models focus on the development of the product life cycle (Kotler, 1971; Wind, 1974). It is true that diffusion models, like any other model, are simplifications of reality. However, they constitute a wide range of useful tools, in both the academic and business context.

"*To use the theory of diffusion as an aid in planning new product introductions, the marketing manager must have a model that represents the process of diffusion for the adoption of his new product*" (Bernhardt and Mackenzie, 1972, p. 193). The value of diffusion models lies in a simplified generalization of the evolution of new products in a market and they can, if used correctly, help managers plan product introductions. Diffusion models also have relevance for the macroeconomy. For example, if we know the specific characteristics of the diffusion process of a certain innovation in a specific sector, this information can be very useful for managers when they have to prepare the introduction of another innovation of similar characteristics in the same sector. This can reduce the uncertainty regarding innovations and contribute to improving results for the sector and for the economy of the country in general.

New product diffusion models have a long history in marketing especially with the seminal paper by Bass (1969). Several studies in management and marketing science have contributed to the development of diffusion theory by suggesting analytical models for describing, forecasting and developing normative guidelines

[5] See Bronnenberg, Mahajan and Vanhonacher (2000), Bronnenberg and Mahajan (2001) and Bronnenberg and Sismeiro (2002) for spatial modeling in marketing.

for the diffusion of an innovation. To identify the models in this area we first introduce some classifications.

Leeflang, Wittink, Wedel and Naert (2000) classify models according to their primary purpose or intended use[6]. They distinguish:
- Descriptive models. These models intend to describe decision processes of managers or customers.
- Predictive models. These models forecast or predict future events or outcomes.
- Normative models. These models are used to obtain recommended or optimal courses of action.

They note that a given model can be intended to be descriptive, predictive and normative. Indeed, one can argue that for a model to have valid normative implications, it must have predictive value and at least some descriptive power. However, a descriptive model need not have normative implications and a predictive model may not be useful for normative considerations. They also point out that it is often logical to proceed from a descriptive to a predictive and then to a normative model. In other situations, a descriptive model may be sufficient.

Many demand models belong to the subset of predictive models. In a demand model, the performance variable is a measure of demand. This performance variable may depend on a number of other variables, such as marketing decision variables employed by the firm and its competitors. We distinguish individual demand models and aggregate demand models. Aggregate demand may refer to:

1. The total number of units of a product category purchased by the population of all spending units. The corresponding demand model is called a model of industry sales, or a model of product class.
2. The total number of units of a particular brand purchased by the population of all spending units. The demand model is then a brand sales model.
3. The number of units of a particular brand purchased by the total population relative to the total number of units purchased of the product class, in which case the demand models is a market share model.

Gatignon and Robertson (1986) identify three types of models, which differ in their objectives and implications:

- Theoretical models. These models offer a mathematical description of a process in which some constructs are systematically joined to others. The objective is to generate theoretical propositions that appropriately describe the possible influence of variables on the diffusion pattern and diffusion rate. These descriptions are the *raison d'être* of theoretical models and should provide suggestions to managers.

[6] See also Leeflang et al. (2000, Chapters 4 and 8).

- Normative models. These models also start with a description and assume functional relationships among the variables that affect the diffusion process. The behavioral assumptions may be less complex than those of theoretical models, given that the objective is not to make descriptive propositions but to develop optimal marketing strategies. An objective function for the firm is determined and the model implications are expressed with respect to variables incorporated into the model. Optimal decisions are the *raison d'être* of normative models.
- Empirical models. The objective of these models is to fit data and test a specific theoretical proposition or a complete model.

Marketing has focused more on empirical and normative than on theoretical models.

Roberts and Lattin (2000) describe a continuum where one extreme is defined by market-level diffusion models (aggregate-level diffusion models) and the other by individual-level diffusion models (disaggregate-level diffusion models). In between these two extremes, it is possible to have a number of intermediate-level models. They define the three categories of models as:

- Aggregate-level diffusion models are those whose objective is to describe market-level behavior without a direct microeconomic derivation of the individual's adoption decision. These models focus on the understanding of the total market development and its response to managerial and environmental variables. The most common approach is to specify the diffusion model at the aggregate level from the outset.
- Individual-level diffusion models are those concerned with the individual adoption process and make little or sometimes no attempt to generalize across the population. These models focus on the process at the level of individual consumers and consider that different members of the population adopt at different times. At the individual level the assumption may be that every potential adopter's hazard rate is different given the idiosyncratic probability of adoption of each member of the population. This disaggregated level approach, relatively recent in the diffusion literature (Chatterjee, Eliashberg and Rao, 2000), begins by considering individual behavior before aggregating across the population, and thus permits explicit consideration of consumer heterogeneity[7].

[7] Disaggregate-level diffusion models are often referred to as adoption models, given that they have the objective to gain insight in the determinants of the individual adoption decision instead of gaining understanding of diffusion process as a whole. In other words, diffusion models describe the adoption of new products from a macro point of view, as an aggregate of individual behavior, whereas adoption models describe the adoption of new products from a micro point of view and describe individual behavior.

- Intermediate-level models allow for restricted differences between individuals in the population. We can restrict the sources of heterogeneity in two ways: one way is to divide the population into discrete homogeneous behavioral groups and look at flows between groups. Another way is to impose other forms of structure on the nature of heterogeneity in the model.

Mahajan, Muller and Bass (1990, 1993) identify three different types of applications for diffusion models. The primary application is sales forecasting. For example, predicting the demand of a certain innovation in the market and hence to gaining insights into its future success or failure. The second is hypothesis testing. For example, diffusion parameters can be used to test hypotheses about differences in the diffusion process of an innovation in several industries. The third type of application concerns normative guidelines. The testing of hypotheses can be realized by the development of a descriptive model. In marketing, the normative use of diffusion models has focused mostly on developing optimal strategies for two marketing variables: price and advertising, and for the timing of product introductions.

The classical diffusion models are aggregate demand models, especially product class sales models. The extensions include brand sales models and others that present a lower aggregation level. This thesis focuses on empirical models (at the aggregate level) that can be used for forecasting and for the evaluation of hypotheses about the dynamics of the diffusion of an innovation (descriptive purpose). Although we are not concerned with normative purposes, the fact that the proposed models are designed to capture the product life cycle of an innovation means that they may also be used to formulate normative guidelines for how an innovation should be marketed.

2.3. Structure of a diffusion model

In this section we provide a general structure of diffusion models. They all have in common the fact that the total market is divided into segments and that the modeling focuses on moving from one segment to the next.

2.3.1. Segments in diffusion models

An "adopter" or an adopting unit is an individual, a family or a group of individuals in the case of consumer products and a company or organization in the case of industrial products. Adoption refers to commitment to and continued use of the new product over time. For durable products, the adoption takes place after the first purchase. For non-durable products, it is necessary for the consumer to make several purchases. Hence, the exact meaning of the term "adopter" depends on the type of product that we consider.

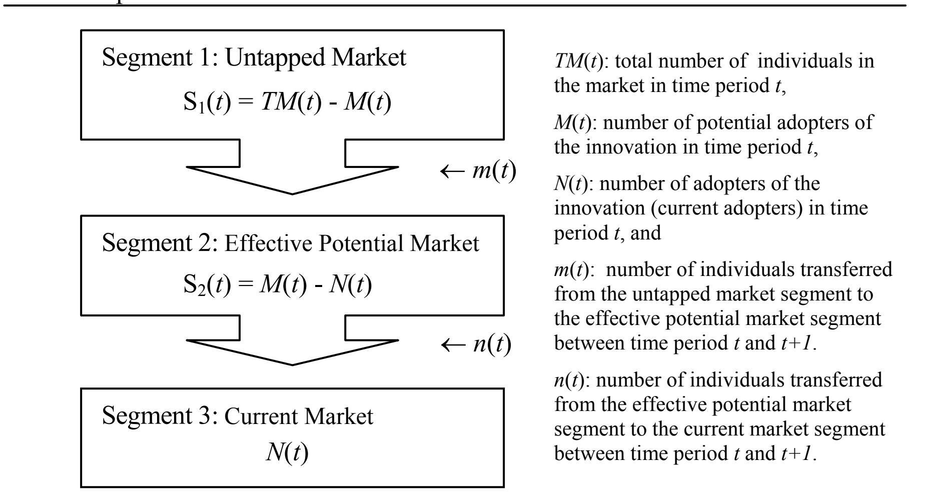
The general structure of a diffusion model considers a situation in which each purchase refers to the sale of one unit of a durable product. As we can see in Figure 2.1, the market is divided into three segments (Mahajan and Muller, 1979):

First Segment: Untapped Market. In this segment, we find consumers who do not know that the innovation exists or who, for whatever reason, are not considered as possible consumers of that innovation in the time period *t*.

Second Segment: Effective Potential Market. In this segment we find consumers from segment one who are now potential consumers of the innovation in the time period *t*.

Third Segment: Current Market. In this segment we find consumers who have already bought the innovation in the time period *t*: the adopters of the innovation.

Figure 2.1.
Consumer flows across the market segment within the diffusion process.
Durable products context.



Source: Adapted from Mahajan and Muller (1979)

A large body of research on diffusion considers flows between consumer segments. The three consumer segments (mentioned above) are represented in Figure 2.1 as:

-Untapped Market- $S_1(t) = TM(t) - M(t)$ (2.1)

-Effective Potential Market- $S_2(t) = M(t) - N(t)$ (2.2)

-Current Market- $N(t)$ (2.3)

where $M(t)$ is the number of potential adopters of the innovation in the time period t, $N(t)$ the number of adopters of the innovation (current adopters) in the time period t, and the total number of individuals in the market in the time period t is:

$$TM(t) = S_1(t) + S_2(t) + N(t). \tag{2.4}$$

The number of individuals in each segment in the time period t+1 is given by the following equations:

$$S_1(t+1) = S_1(t) + tm(t) - m(t) \tag{2.5}$$

$$S_2(t+1) = S_2(t) + m(t) - n(t) \tag{2.6}$$

$$N(t+1) = N(t) + n(t) \tag{2.7}$$

where $m(t)$ is the number of individuals transferred from the untapped market segment to the effective potential market segment between time period t and t+1, $n(t)$ is the number of individuals transferred from the effective market potential segment to the current market segment between time period t and t+1, and $tm(t) = TM(t+1) - TM(t)$ the increase of the total number of individuals in the market. Hence, we also can obtain $tm(t) = s_1(t) + s_2(t) + n(t)$ where

$$s_1(t) = tm(t) - m(t) \tag{2.8}$$

$$s_2(t) = m(t) - n(t) \tag{2.9}$$

where $s_1(t) = S_1(t+1) - S_1(t)$ and $s_2(t) = S_2(t+1) - S_2(t)$.

Previous equations characterize flows among consumer segments in the diffusion process of innovations and constitute the basis of the classical diffusion models and some extensions of these models (Mahajan and Muller, 1979). In most models the flow of consumers from the second segment to the third segment is studied: the number of adopters at time t -$n(t)$-. Although we have shown the general structure of the diffusion process proposed by Mahajan and Muller (1979), it can be modified according to the individual researcher's focus. Although we do not review every possible scenario, we show the proposal of Hahn, Park, Krishnamurthi and Zoltners (1994) for non-durable products (see Figure 2.2). The authors divide the market into four consumer segments:

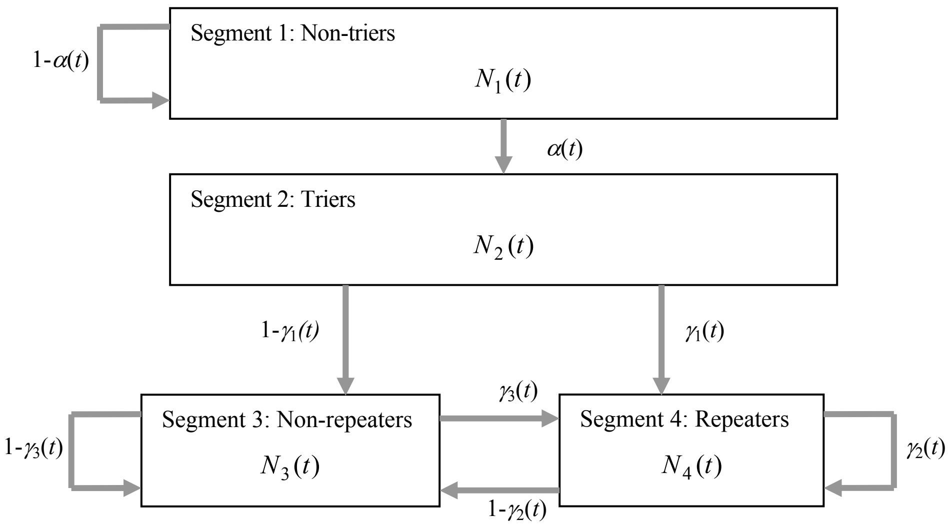
First Segment: Non-triers. In this segment we find potential consumers who have not tried the innovation at time t.

Second Segment: Triers. In this segment we find consumers who had not tried the innovation by the time period t-1 but try the innovation at time t.

Third Segment: Non-repeaters. In this segment we find consumers who have tried the innovation at some time before time *t*, but are not repurchasing the product at time *t*.

Fourth Segment: Repeaters. In this segment we find consumers who have tried the innovation at sometime before time *t*, and are repurchasing it at time *t*.

Figure 2.2.
Consumer flows across the market segment within the diffusion process.
Non-durable products context.



$N_i(t)$: number of consumers in segment *i* in the time period *t*, i = 1,2, 3 and 4,
$\alpha(t)$: fraction of non-triers in the time period *t*-1 who try the innovation in *t*,
$\gamma_1(t)$: fraction of triers in the time period *t*-1 who repurchase the innovation in *t*,
$\gamma_2(t)$: fraction of repeaters in the time period *t*-1 who repurchase the innovation in *t*, and
$\gamma_3(t)$: fraction of non-repeaters in the time period *t*-1 who repurchase the innovation in *t*,

Source: Adapted from Hahn, Park, Krishnamurthi and Zoltners (1994)

The following system of equations describes the trial-repeat framework in Figure 2.2:

$$N = N_1(t) + N_2(t) + N_3(t) + N_4(t) \qquad (2.10)$$

$$Y_i(t) = N_i(t) + N_{i+2}(t) \text{ for } i = 1,2 \qquad (2.11)$$

where *N* represents the total number of potential consumers of the product, and $Y_i(t)$ divides consumers into non-triers and non-repeaters (*i*=1), and buyers (*i*=2) in the time period *t*. The dynamic relationships that govern the trial structure are:

$$N_1(t) = \left[1 - \alpha(t)\right] N_1(t-1) \tag{2.12}$$

$$N_2(t) = \alpha(t) N_1(t-1) \tag{2.13}$$

where $\alpha(t)$ is the fraction of non-triers in the time period t-1 who try the innovation in t. The dynamic flows through the innovation trial segment and the two post-trial segments are described by

$$N_3(t) = \left[1 - \gamma_1(t)\right] N_2(t-1) + \left[1 - \gamma_2(t)\right] N_4(t-1) + \left[1 - \gamma_3(t)\right] N_3(t-1) \tag{2.14}$$

$$N_4(t) = \gamma_1(t) N_2(t-1) + \gamma_2(t) N_4(t-1) + \gamma_3(t) N_3(t-1) \tag{2.15}$$

where $\gamma_1(t)$, $\gamma_2(t)$ and $\gamma_3(t)$ are the fractions of triers, repeaters and non-repeaters in the time period t-1 who repurchase the innovation in t, respectively. This context also allows for switching between the last two segments (the post-trial segments). Hahn et al. (1994) use this framework to propose an extension of the classical diffusion model (designed for durable innovations) to analyze non-durable innovations when repeat purchases are allowed.

If we understand the movement of individuals from one segment to another, it is easier to understand the mathematical development of classical diffusion models and their extensions. This is our focus for the rest of this chapter.

2.3.2. Modeling diffusion

A diffusion function is usually defined as the solution $y = y(t)$ of a differential equation: $dy/dt = f(y,t)$ where the function f determines the shape of the diffusion curve, which usually comes from the assumptions made regarding the nature of the diffusion process of an innovation within the market, the function y describes how the diffusion process evolves over time and t time.

Using the terminology commonly used in the context of the diffusion of innovations (Mahajan and Schoeman 1977; Kalish and Sen, 1986; Mahajan, Muller and Bass, 1990, 1993) we arrive at a mathematical expression for a basic or fundamental diffusion model. We assume that the rate of diffusion or the number of adopters at any time is directly proportional to the number of potential adopters at that moment. Mathematically, this can be represented as[8]:

$$n(t) = \frac{dN(t)}{dt} = g(t)\left[M - N(t)\right] \tag{2.16}$$

[8] The diffusion process is evidently stochastic in nature; however, we follow the usual approach in marketing literature in restricting our attention to the derivation of the deterministic version. See Bartholomew (1973) for the standard technical arguments for proceeding from the stochastic version to the analogous deterministic version. The literature of diffusion assumes that: i) N(t) and $n(t)$ are continuous functions and their derivatives exist at all points, and ii) $n(t)$ is an unimodal function.

where $N(t)=\int_{t_0}^{t} n(t)dt$ (2.17)

and $n(t)$ is the number of adopters at time t, $N(t)$ is the cumulative number of adopters at time t, M is the potential market (total number of potential adopters in the social system or, in other words, the upper limit of the total number of adoptions that are possible), the difference $[M\text{-}N(t)]$ indicates the potential adopters that are available at that moment of time (the effective potential market). When $N(t)$, the cumulative number of adopters at time t, approaches M, the total number of possible adopters in the social system, the diffusion rate decreases.

The parameter of diffusion $g(t)$, also known as the rate of adoption or individual probability of adoption, indicates the probability that a random potential adopter adopts the innovation at time t. The parameter $g(t)$ can be interpreted as a conversion parameter or a transfer mechanism of a potential adopter to an effective adopter: the rate at which the adoption of the innovation takes place and, therefore, the response rate of the non-adopters.

Traditionally, the literature of diffusion of innovations has represented[9] $g(t)$ as a linear function of $N(t)$:

$$g(t)=a+bN(t)\,. \tag{2.18}$$

Substituting (2.18) in (2.16) we have an expression for a *fundamental diffusion model* (Mahajan and Peterson, 1985):

$$n(t)=\left(a+bN(t)\right)\left[M-N(t)\right] \tag{2.19}$$

where the parameters a and b show the degree of intensity of the source of external and internal influence, respectively. The parameter of external influence, a, is determined by two components: i) the intrinsic tendency of the individual (person or firm) to innovate, and ii) external communication. The parameter of internal influence, b, shows the impact on the adoption of the innovation of personal contact with previous adopters (word-of-mouth communication). The term $a[M\text{-}N(t)]$ represents adoptions resulting from external influence, and the term $bN(t)[M\text{-}N(t)]$ represents adoptions resulting from interactions between adopters, $N(t)$, and non-adopters, $[M\text{-}N(t)]$.

In general, communication channels are (along with time, the innovation, the social system and marketing) a vital element in the diffusion process of any

[9] It is possible to represent $g(t)$ either as a function of time (Souden and Quaddus, 1982) and as a function of the number of previous adopters. Due to the fact that diffusion models describe the rate of adoption by focusing the adoption process, it seems logical that they model the number of adopters through time. As Mahajan and Peterson (1985) point out, although $g(t)$ can be expressed as a function of $N(t)$, $g(t) = a + bN(t) + cN(t)^2 + \ldots$ but reasons of analytical parsimony and the facility to interpret and estimate the parameters, take $g(t)$ to be formulated considering only the two first addends on the right side of the equation.

innovation. Communication channels constitute the means through which the innovation expands among the members of a social system. We make a distinction between external communication (for instance, through advertising or explanations from sales representatives), which is very effective in the first steps of the adoption process and internal communication (interpersonal communication, interaction among members of a social system), which is more suited to influencing behavior when the adoption process has already started. Both forms of communication are complementary and they can play different roles during the adoption process. The importance or intensity of the influence that both forms of communication have on the members of the social system not only differs according to the characteristics of the innovation but also the characteristics of the agents within the social system.

The influence that previous adopters of an innovation exercise on potential adopters by persuading them to imitate them in their decision to adopt the innovation (interaction effect, imitation effect), helps to explain the acceleration of the diffusion process as a logical process. If the decision to adopt is subjected to social influence, contact between both adopter types (effective and potential) leads to a situation in which the probability of a potential adopter adopting the innovation at a certain moment of time depends on the number of previous adopters. Depending on the importance of one or the other source of influence, different versions can be derived from the fundamental diffusion model (Mahajan and Peterson, 1985) represented by Equation (2.19):

Diffusion model of external influence when b=0

$$n(t) = \frac{dN(t)}{dt} = a\left[M - N(t)\right] \tag{2.20}$$

Diffusion model of internal influence when a=0

$$n(t) = \frac{dN(t)}{dt} = bN(t)\left[M - N(t)\right] \tag{2.21}$$

Mixed influence diffusion model when a≠0 and b≠0

$$n(t) = \frac{dN(t)}{dt} = \left(a + bN(t)\right)\left[M - N(t)\right]. \tag{2.22}$$

Appendix 2A provides detailed explanations of the three specifications of the fundamental diffusion model. In the above specifications, the implicit importance of uncertainty stands out as an explaining element of the diffusion process. Knowledge of the existence of an innovation is not enough for an individual to become a potential adopter and finally adopt the innovation. The influence of external sources and/or the experience of previous adopters are basic elements in the reduction of uncertainty and, therefore, in the risk perceived by individuals.

In order to determine the form of $g(t)$ in the mixed influence diffusion model, its equivalence in the Bass (1969) model is taken. The Bass model is the most parsimonious aggregated diffusion model suggested in marketing literature (Parker, 1994) and it has large acceptance in the field of innovation diffusion (Mahajan, Muller and Wind, 2000). Since its publication, several hundred articles have been written on the applications and extensions of the model (Mahajan, Muller and Bass, 1990, 1993; Sultan, Farley and Lehmann, 1990). The Bass model constitutes a model that is used to the formulation of *empirical generalizations* in marketing (Bass, 1993, 1995). Mathematically, the central idea of the Bass model is that the conditioned probability of an individual adopting at time t, given that this individual has not already adopted, is a linear function of the number of previous adopters:

$$\frac{f(t)}{\left[1-F(t)\right]} = p + qF(t) \tag{2.23}$$

where the random variable t denotes the moment of adoption of a new product by an individual (adopter), $f(t)$ is the probability of adoption at time t, $F(t)$ the cumulative distribution function and, p and q are the parameter of innovation and imitation respectively. If we define M as the potential market of adopters, $n(t)$ as the number of adopters at time t, with $n(t)=Mf(t)$, and $N(t)$ the cumulative number of adopters at time t, without including t ($N(t)=MF(t)$), we can express the Bass model as:

$$n(t) = \left(p + q\frac{N(t)}{M}\right)\left[M - N(t)\right]. \tag{2.24}$$

Hence the parameter of proportionality $g(t)$ in (2.16) is equal to $p + q\dfrac{N(t)}{M}$.

It is easy to see that the Bass model is the general fundamental mixed influence diffusion model (Equation (2.22)) with a little modification[10].

In order to avoid misinterpretations[11] in the three specifications of the fundamental diffusion model that will be used in this study and to facilitate the understanding of the extensions of this model when more parameters are included, $g(t)$ is finally represented in the following terms:

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[10] This can be seen as follows. We multiply Equation (2.23) by M, replace $F(t)$ with $N(t)/M$, $f(t)$ with $n(t)/M$ and rearrange the terms to obtain: $n(t) = \left(p + q\frac{N(t)}{M}\right)\left[M - N(t)\right]$.

[11] Bhargava, Bhargava and Jain (1991) emphasize the necessity of interpretational consistency in model equations.

- $g(t) = \beta_1 + \beta_2 \dfrac{N(t)}{M}$ in the *mixed influence diffusion model*
- $g(t) = \beta_1$ in the *diffusion model of external influence*
- $g(t) = \beta_2 \dfrac{N(t)}{M}$ in the *diffusion model of internal influence*.

where β_1 is the parameter of external influence and β_2 the parameter of internal influence[12].

2.4. Assumptions behind traditional diffusion models

2.4.1. Criticism of innovation diffusion research

There is much criticism of research on the diffusion of innovations[13]. Most of them refer to the applied estimation procedure, the type of product analyzed or the vast use of aggregate data.

Estimation procedures

Sultan, Farley and Lehmann (1990), in their meta-analysis of applications of diffusion models, find that the parameters of external and internal influence are slightly affected by estimation methods. They, together with other researchers, suggest the need for a systematic study of estimation methods because the selected estimation method[14] depends on the specification of the diffusion model and the available data. Mahajan, Muller and Bass (1990, 1993) classify diffusion model estimation procedures into two groups:

1) time-invariant estimation procedures, such as OLS (ordinary least squares), MLE (maximum-likelihood estimation), NLLS (nonlinear least squares) and AE (algebraic estimation); and
2) time-varying estimation procedures, which can be characterized into three groups (Putsis and Srinivasan, 2000):
    2.1) systematic (non-stochastic) variation models,

[12] Some authors prefer referring to β_1 and β_2 as parameters of external and internal influence, respectively, following Lekvall and Wahlbin (1973); others prefer referring to them as parameters of innovation and imitation influence, respectively, following Bass (1969).
[13] See also Bernhardt and Mackenzie (1972), Heeler and Hustad (1980), Mahajan, Muller and Bass (1990, 1993), Van den Bulte and Lilien (1997) and Bemmaor and Lee (2002).
[14] See Putsis and Srinivasan (2000) for an exhaustive revision of estimation procedures for macro diffusion models.

2.2) stochastic stationary processes -such as Feedback filters, Bayesian approaches, Kalman filters, AKF(C-D) (augmented Kalman filter with continuous state and discrete observations)-, and
2.3) stochastic non-stationary processes -such as the Cooley-Prescott procedure-.

Most researchers have chosen NLLS as diffusion model estimation procedures. Putsis and Srinivasan (2000, p. 285) point out that "*NLLS applied to non-cumulative sales has become the de facto standard in diffusion research and should be preferred in single-equation time-invariant setting since (1) empirical evidence suggests that NLLS provides for a better fit and lower forecast errors for durable product categories and (2) the existence of a downward bias in MLE standard error estimates"*. Also, they suggest that, as it is unlikely that the parameters in a diffusion model will be constant over time, "*varying parameter estimation should be used more frequently*" (we address this issue in Chapter 6).

Type of product analyzed

Diffusion models mainly focus on consumer durables, especially at the category level. A diffusion model gives the time path of growth for the number of adopters of a new product. When we analyze a new durable at the category level, we can translate this into a corresponding time path for sales. However, this translation is not easy at the brand level when there are close substitutes, given that "*an adopter may switch from one of these substitutes to another without settling on any, or he may decide to buy one more than another*" (Bernhardt and Mackenzie, 1972, p. 198). This is also a common situation for frequently purchased products. Hence, more research on diffusion models at the brand level focusing on frequently purchased products is required (Sultan, Farley and Lehmann, 1990; Parker, 1994; Krishnan, Bass and Kumar, 2000). More specifically, Krishnan, Bass and Kumar (2000, p. 269) point out three possible reasons for the dearth in research on brand-level diffusion:

"*(1) the belief that the theory underlying the diffusion process (i.e., the sociocontagion theory) is most applicable to a category, not to its brands;*
(2) the fact that the sales of a brand in a new category are affected by multiple factors (such as category-level diffusion, marketing-mix variables such as price and advertising of each brand in the market, and different entry times of the various brands);
(3) the nonavailability of appropriate data to test the models"

Aggregate data

The large number of studies that have emerged since the pioneer aggregate-level diffusion model by Bass (1969) has demonstrated the ability of aggregate-level models to fit macrolevel data and to provide an understanding of the drivers of sales over time. Aggregate-level data are more available for companies and researchers, while market-research data (disaggregate-level data) about preferences and behavioral intentions collected from respondents are not. Data availability is an important factor in limiting the application of individual-level models. Roberts and Lattin (2000, p. 220-221) point out that "*individual-level dynamic-diffusion models provide a useful theoretical perspective from which to attempt to generalize across consumers and also a flexible way of incorporating as rich a degree of consumer heterogeneity as is required. Marketing-mix variables are incorporated in a rigorous way, and segmentation can be performed on any basis. This comes at a cost of lack of parsimony and also the market-level application of these individual models are not as obvious",* and they suggest that more work on the intermediate-level models is interesting, given that these models have "*the richness, rigor of prelaunch calibration, and theoretical grounding of individual-level models, while maintaining some of the parsimony and market-level interpretation of the aggregate-diffusion modeling approach*" (Roberts and Lattin, 2000, p. 223).

Other assumptions behind the classical diffusion models are also criticized. In the remainder of this chapter we will pay attention to this issue. Our empirical analyses focus on relaxing some of the assumptions behind the diffusion models and widening the application field of diffusion models to products other than the traditional consumer durables.

The original diffusion paradigm from behavioral theory (Rogers, 1962) assumes that an innovation emanates from a source and diffuses unchanged over time among potential adopters. This implies that much of the process innovations go through during diffusion is ignored, which affects the way the diffusion process is modeled. Diffusion models of new products are based on several simplifying behavioral assumptions (Mate, 1981). This section reviews the well-known assumptions (Table 2.1) behind the classical diffusion models and the studies that attempt to relax these assumptions[15].

The fundamental diffusion model (in its three versions) is based on several assumptions (see Table 2.1) that, although reducing the realistic nature of the innovation diffusion process, provide model analytical solutions. We discuss each of these assumptions in more detail in Section 2.4.2.

Many researchers performed studies that relax one or more of the restrictive assumptions. Appendix 2B shows some tables (Table 2B) that summarize the most relevant works, indicating which assumption is relaxed by each work.

[15] Mahajan and Peterson (1985), Mahajan, Muller and Bass (1990, 1993), Mahajan, Muller and Wind (2000), and Fildes and Kumar (2002) provide excellent the state-of-art reviews of diffusion models.

Table 2.1.
Basic conceptual assumptions on which the fundamental or basic diffusion model is based

During the diffusion process ……….
1. which is a binary process, population is homogeneous
2. the size of the adopter population does not change,
3. the parameters of external and internal influence remain constant,
4. only one adoption per adopter is allowed,
5. geographical frontiers do not vary,
6. the innovation is diffused in isolation,
7. the characteristics of an innovation and its perception do not alter,
8. there are no supply restrictions,
9. the impact of the marketing variables used to diffuse an innovation is implicitly captured by the model parameters.

We pay attention to the following issues:
1. The enlargement of the number of segments in order to better understand the dynamics behind the diffusion process.
2. The dynamics of the potential market, which changes with the environment within which the diffusion process develops.
3. The dynamics of the diffusion parameters (external and/or internal influence), which allows for analyzing and comparing several strategies in different situations.
4. The relevance of incorporating repeat purchases.
5. The possibility of a non-static geographical context during the diffusion process.
6. The relaxation of the assumption that states that innovation is introduced by only one firm in a market where there is no competition.
7. The importance of considering the innovation characteristics and its perception by the social system members.
8. The possible supply restrictions that can condition the diffusion of an innovation in the market.
9. The explicit incorporation of marketing variables in the model.

We review each of the assumptions behind the fundamental diffusion model. Although we highlight the importance of relaxing each assumption and discuss studies in which one or more assumptions are relaxed, we discuss the assumptions relaxed in our empirical analyses (Chapters 4, 5 and 6) in more detail.

2.4.2. Discussion on assumptions

We discuss each of the basic assumptions on which the fundamental or basic diffusion model is based.

2.4.2.1. Assumption 1. The diffusion process is a binary process and population is homogeneous

According to this assumption, consumers who enter the potential market have two options: to adopt or reject the innovation. As a consequence, adoption is treated as discrete as opposed to continuous behavior. The basic diffusion model considers that the diffusion process is binary (two-stage or binary population) and disregards the different stages[16] of an adoption process i.e. from lack of awareness of the innovation to adoption. Although an adoption model better captures individual behavior, a diffusion model wins on simplicity and parsimony (Mahajan, Muller and Kerin, 1984). However, since the mid 70s, various authors have worked on bringing these two kinds of models closer together. Examples are the studies of Midgley (1976), Dodson and Muller (1978), Mahajan and Muller (1982), Sharif and Ramanathan (1982), Mahajan, Muller and Kerin (1984), Kalish (1985), Bayus (1987), Jain, Mahajan and Muller (1991) and Ho, Savin and Terwiesch (2002), who extend the basic diffusion model by increasing the number of stages[17] in the adoption process and creating *polynomial, multinomial, multi-state* or *multi-stage diffusion models*.

By increasing the number of stages, these models relax the homogeneity of the population. In this way, it becomes possible account for situations in which there are individuals who present active, passive or neutral attitudes when assessing the innovation (Midgley, 1976)[18], those who reject it due to disappointment after having formed expectations of it or even those who reject it before trying (Sharif and Ramanathan, 1982).

Although these models offer a more realistic representation than the models that consider only two stages[19], they are complicated to work with. They require very detailed information on consumer movements through the various adoption process

[16] See Rogers (1983) for an extensive review of the evidence for various stages in the adoption process of an innovation.

[17] See also Nijkamp (1993) for an extensive review and discussion of new product macroflow models.

[18] Silver (1984) develops a comprehensive discussion of Midgley's (1976) paper given the significance of Midgley's diffusion research.

[19] This does not mean that binomial models are not correctly applied in certain situations; for example, in a situation in which there is so much information on the innovation that all individuals know about its existence and only have to decide whether to adopt it or not.

stages, and they can have estimation problems[20]. Dodson and Muller (1978), for example, develop a theoretical model with no empirical application because they have mathematical treatment problems. Whereas Dodson and Muller assume implicitly that individual experience of an innovation is positively communicated through social interaction, other multi-stage models include the possibility of positive or negative communication (Mahajan, Muller and Kerin, 1984) or even neutral (Midgley, 1976; Mahajan and Muller, 1982).

Kalish (1985) divides the diffusion process into awareness and adoption, and provides a model for each process. In this way he is able to account for a population that is heterogeneous with respect to the valuation of the new product. Awareness is modeled with a mixed influence diffusion model where advertising is explicitly considered to affect external influence. To model adoption, Kalish proposes an awareness conditional model in which the perceived risk adjusted value of the product is taken into account.

Bayus (1987), focusing on new contingent[21] product sales, considers that market segments with different buying behaviors are expected to exist within the potential market. Within these segments, some fractions will be aware of the innovation, and a smaller proportion will have positive purchase intentions.

Jain, Mahajan and Muller (1991) and Ho, Savin and Terwiesch (2002), consider the presence of supply restrictions. They extend the mixed influence diffusion model from a two to a three stages model, given that customers flow from potential adopters to waiting applicants and then from applicants to adopters.

Midgley (1976) applies his model to non-durable consumer products such as toothpaste, detergents and biscuits. Mahajan and Muller (1982) do not present any empirical application. Sharif and Ramanathan (1982) provide an application on televisions. Mahajan, Muller and Kerin (1984) present an application for a movie. Kalish (1985) illustrates an application of his model to a durable good (without specifying it). Bayus (1987) presents a study of the compact disc prerecorded audio market. Jain, Mahajan and Muller (1991) test their model on telephone adoption data, and Ho, Savin and Terwiesch (2002) present the results of a numerical study.

The fundamental diffusion model implicitly assumes that the population of potential adopters is homogenous; i.e. that all individuals behave equally when deciding whether or not to adopt an innovation. One way to relax this restriction is though multi-stage diffusion models. Another possibility is to specify a model that

[20] "*For the multistage or polynomial diffusion models to be useful, it is necessary that proper data gathering and estimation procedures be developed and established*" (Mahajan and Wind, 1986. p. 15).
[21] "*contingent: sales of one product are conditional upon those of other products*" (Peterson and Mahajan, 1978, p.208).

includes a parameter that permits heterogeneity of individuals with regard to their susceptibility to an innovation. The incorporation of this new parameter into the model not only allows for heterogeneity among adopters, but also introduces flexibility into the model allowing it to adapt to different diffusion patterns.

Examples of studies that take into account heterogeneity of the population are Jeuland (1981), Gore and Lavaraj (1987), Tanny and Derzko (1988), Parker (1992, 1993) and Bemmaor and Lee (2002).

Jeuland (1981) proposes a model in which he aggregates different homogeneous segments of adopters, and where adoption rates vary from segment to segment. Specifically, Jeuland (1981) extends the mixed influence model by adding a parameter to the effective potential market which allows for differences among adopters in their propensities to adopt an innovation (this model is discussed in more detail in Chapter 5). Gore and Lavaraj (1987) base their study on the diffusion of an "innovation" (crossbred goats) in a spatially stratified community with asymmetric communication. Tanny and Derzko (1988) propose a model where the adoption process for innovators and imitators (the two subgroups on the population) are individually modeled. Parker (1992), following Jeuland (1981), introduces the parameter of heterogeneity into his mixed influence diffusion model in a study of the diffusion patterns of sixteen consumer durables. However, only with two of these products (irons and black and white televisions), the parameter of heterogeneity is significant. Parker (1993), in his analysis of nineteen durable goods, finds that the parameters of external and internal influence are difficult to estimate when the model contains a heterogeneity parameter, and as a general rule, the elimination of this parameter from the model yields plausible parameter estimates. Bemmaor and Lee (2002) extend the Bass model introducing a parameter that represents the level of consumer heterogeneity. They test their model on simulated data and on twelve real adoption data sets (consumer products and services). Their results show that their flexible model provides a better fit to the data and better one-step ahead forecasts than the Bass model.

Other studies that relax the assumption of a homogeneous population are discussed when we elaborate on assumption 7.

In summary, researchers have found various adopter behavior patterns that result in different buying behavior. This means that individuals can be grouped into more classes than simply adopters and non-adopters. Hence, among adopters, different diffusion patterns can be drawn, as opposed to the single pattern suggested by the basic diffusion models. This encourages researchers to continue addressing assumption 1 by increasing the number of stages through which an adopter passes from lack of awareness of a new product to its adoption or by including an additional parameter into the model that controls heterogeneity of adopters regarding innovations.

2.4.2.2. Assumption 2. The population of adopters does not vary

The basic diffusion model assumes that the size of the social system is fixed, finite and known or can be estimated. It seems illogical to imagine a diffusion process in which the size of the social system remains stable through time, as there are many exogenous factors (such as economic, social or technological conditions) and endogenous factors (such as product improvements, advertising campaigns or changes to distribution channels) that could affect it.

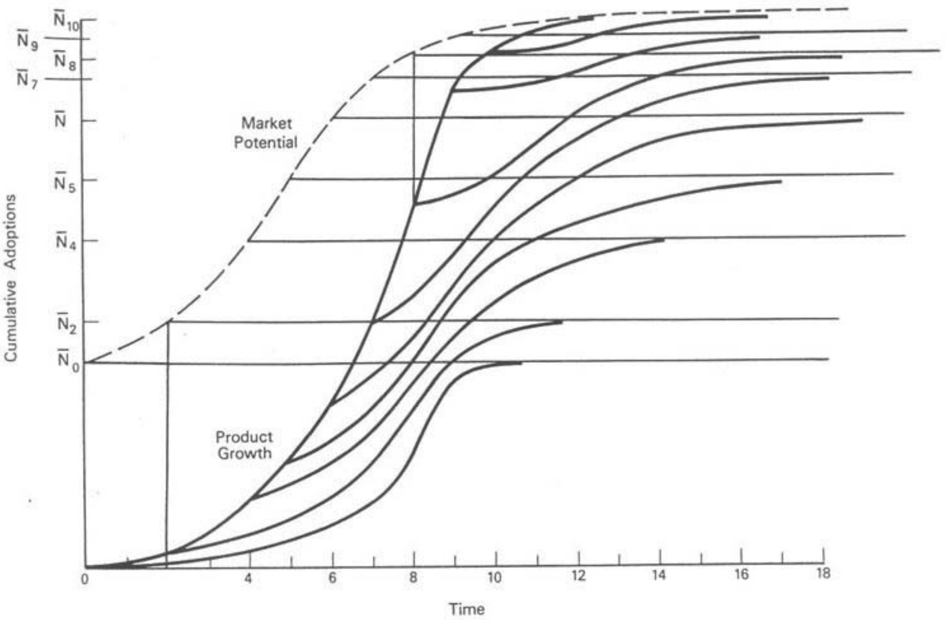
Sharif and Ramanathan (1981) present good reasons for considering the case in which the size of the potential market changes over time. They point out that if the demand for the output generated by innovations grows over time, the number of potential adopters will also grow. They demonstrate that technological innovations are a particularly strong motivation for the entry of new companies. Moreover, they show that improvements on innovations widen their practical applications and increase the number of potential users over time[22].

The precision of a dynamic diffusion model depends, to a large extent, on identifying the variable(s) that affect $M(t)$ and on determining the way in which they affect: $M(t)=f(V(t))$; where $V(t)$ is a vector of all the potentially relevant exogenous and endogenous variables (both controllable and uncontrollable) that affect $M(t)$, and $f(.)$ is the functional shape of this influence. A sensible selection of these variables can help explain and clarify the reasons why the diffusion process of one innovation is much faster or slower than that of another. The decision on which and how many variables need to be incorporated into $V(t)$ depends on various aspects, both conceptual (for example, the characteristics of the innovation or market) and pragmatic (for example, the availability of relevant data).

Figure 2.3 shows the diffusion curve of an innovation when $M(t)$ grows over time. As can be seen, when we consider a dynamic mixed influence diffusion model the ceiling of the cumulative number of adoptions, $M(t)$, is dynamic and grows over time; and the difference between the cumulative number of adoptions and the product growth curve decreases over time until the two curves finally meet.

[22] See also Brown (1981).

Figure 2.3.
Diffusion process with a dynamic potential market.



Source: Mahajan, Peterson, Jain and Malhotra (1979)

Various authors have worked on relaxing this assumption. Table 2.2 summarizes these studies, specifying the influence type considered (external, internal or mixed), the innovation type and the way the dynamic potential market is specified.

Dodson and Muller (1978) develop two models that extend the mixed influence model. The first is a dynamic mixed influence model with advertising and social interaction (word-of-mouth) while the second extends the first by incorporating repeat sales and brand switching. The movement from unawareness of the product to awareness is considered to be a function of a firm's advertising expenditure. However, they do not provide details on the estimation procedure, data sources, estimation or specification of initial awareness and advertising response function.

Mahajan and Peterson (1978, 1982) consider the mixed influence diffusion model and assume a potential market that varies with certain variables. They propose the following model:

$$\frac{dN(t)}{dt} = \left(a + bN(t)\right)\left[f(V(t)) - N(t)\right], \tag{2.25}$$

where $N(t = t_0) = N_0$, $f(V(t_0)) = f_0$. A solution for (2.25) is

$$N(t) = -\frac{a}{b} + \frac{\exp\left(a(t - t_0) + bM(t)\right)}{\left(\frac{b}{a + bN_0}\right) + b\int_{t_0}^{t} \exp(a(x - t_0) + bM(x))dx} \tag{2.26}$$

where $M(t) = \int_{t_0}^{t} f(V(x))dx,$

and $N(t)$ is the cumulative number of adopters at time t, $f(V(t))$ is a function of relevant variables affecting the potential market at time t and a and b are the parameters of external and internal influence, respectively. Mahajan and Peterson (1978) analyze the diffusion of membership of the United Nations and the diffusion of washing machines in the United States. Only one factor is considered to affect the potential market:

$$M(t) = f(HH(t)) = \delta_1 + \delta_2 HH(t) \tag{2.27}$$

where $HH(t)$ is the number of housing starts in the United States at time t for washing machines or the number of countries in the world at time t for United Nations membership, δ_1 and δ_2 are constants. Their model performs quite well for both examples.

Mahajan, Peterson, Jain and Malhotra (1979) apply the dynamic diffusion model of Mahajan and Peterson (1978) (with a parameter of external influence a=0) to represent the growth of three consumer durables (gas cookers, washing machines and gas water heaters) during the period 1948-1973. They consider that the ceiling of the cumulative adoptions (the potential market) changes over time as a result of the increase in the number of housing starts in the United States. They employ the same function as Mahajan and Peterson (1978) to account for the dynamics of a potential market. The dynamic model performs rather well in all three product applications.

Sharif and Ramanathan (1981) specify three models (one for each influence type: external, internal and mixed) with various specifications for $M(t)$:

$$M(t) = M_0 e^{\delta_1 t} \tag{2.28}$$

$$M(t) = M_0(1 + \delta_2 t) \tag{2.29}$$

$$M(t) = \frac{\delta_3}{1 + \delta_4 e^{-\delta_5 t}} \tag{2.30}$$

$$M(t) = \delta_6 - \delta_7 e^{-\delta_8 t} \tag{2.31}$$

where M_0 >0 (size of the potential market at the time of product introduction), δ_1, δ_2, δ_3, δ_4, δ_5, δ_6, δ_7 and δ_8 are positive constants. They suggest that Equations (2.28) and (2.29) would be useful for short and medium-term forecasting since in the long term an unlimited increase of potential adopters is not compatible with the diffusion situation. They suggest that Equations (2.30) and (2.31) can be used for long-term forecasting as well because they show that the population of potential adopters is itself a monotonically increasing function of time with an upper limit. The authors provide three applications: one for a community innovation (fluorinated water), another for a firm innovation (credit-card banking) and a third for a consumer innovation (oral contraceptive). Their results show the superiority of the proposed models, in comparison with existing models, in terms of forecasting accuracy.

Feichtinger (1982) extends the mixed influence model by assuming that potential market is a function of price. Feichtinger shows the applicability of his model through a phase portrait analysis.

Jorgensen (1983) assumes that potential market is a linear-decreasing function of price. Neither empirical nor numerical results are provided.

De Palma, Droesbeke and Lefevre (1984) develop a generalization of the mixed influence diffusion model in which the size of the potential market depends on the selling price. In their analysis they consider two specifications for the dynamic potential market. In the first case, they assume that:

$$M(t) = f(P(t)) \tag{2.32}$$

where $P(t)$ is price at time t and $f(.)$ the functional form of the influence of price on the potential market. They do not specify any functional form. In the second case they assume that:

$$M(t) = M + \left(\frac{\delta_1}{P(t)}\right)^{\delta_2} \tag{2.33}$$

where M represents those who are not influenced by the price (called the "systematic" potential market), $P(t)$ the price at time t, δ_1 the "non-systematic" potential market expressed in monetary units and $\delta_2 \geq 0$ the price effect "power". The authors do not present any empirical application.

Kalish (1985) proposes a two-stage diffusion model where potential market depends on current price ($P(t)$) and uncertainty ($U(t)$). He proposes the following specification for potential market:

$$M(t) = f\left(\frac{P(t)}{U(N(t)/M_0)}\right) \tag{2.34}$$

where $f\left(P(t)\right) = M_0 e^{-\delta_1 P(t)}$, $U\left(\frac{N(t)}{M_0}\right) = \frac{\delta_2 + \left(\frac{N(t)}{M_0}\right)^2}{\delta_2 + 1}$, M_0 is the size of the potential market at the time of product introduction and δ_1 and δ_2 are a constant.

Kalish (1985) tests his model on an unspecified consumer durable and demonstrates that his model provides a good fit.

Olson and Choi (1985) extend the model of mixed influence diffusion by incorporating replacement and a dynamic potential market. They use one of the specifications proposed by Sharif and Ramanathan (1981) (Equation (2.28)) for the dynamic potential market (they assume that the population grows at a constant rate). Their model is tested on four durable products (black and white televisions, color televisions, clothes dryers and dishwashers). They compare their model with the logistic model. Their results show that only for dishwashers, the proposed model performs worse than the logistic model.

Kalish and Lilien (1986a, 1986b) also extend the mixed influence model. They assume that the potential market is dynamic in the following way:

$$M(t) = M_0 e^{-\delta P(t)} \tag{2.35}$$

where $P(t)$ is the price at time t, and M_0 and δ are parameters to be estimated. The authors test their model on a new durable product (a photovoltaic system) and the results show that the fit is good and the parameters have correct signs, good significance levels (two of the three parameters are significant) and proper magnitudes.

Bayus (1987), following Lawrence and Lawton (1981), extend the mixed influence diffusion model by modeling the potential market as a function of several variables:

$$M(t) = \sum_{j=1}^{J} HH(t) SEG_j(t) AWARE_j(t) INTENT_j(t) \tag{2.36}$$

where $HH(t)$ is the total number of households at time t, $SEG_j(t)$ the proportion of $HH(t)$ that is in segment j at time t, $AWARE_j(t)$ the proportion of segment j that is aware of the product at time t, $INTENT_j(t)$ the proportion of segment j that is aware of the product and has positive purchase intentions at time t, and J the number of market segments. A study of the compact disc prerecorded audio market is used in a practical application of this model.

Kamakura and Balasubramanian (1987) extend the mixed influence diffusion model. They incorporate price in the model affecting potential market:

$$M(t) = \delta_1 HH(t) P(t)^{\delta_2} \tag{2.37}$$

where $HH(t)$ is the number of electrified homes at time t, $P(t)$ is the price index at time t (therefore $P(1)=1$), δ_1 is the final penetration (or the proportion of the total number of homes expected to adopt the product) if price were kept at its original level and δ_2 represents the impact of price. They test their model on four consumer durables (refrigerators, vacuum cleaners, toasters and electric blankets). Their results show that although the price parameter has the expected negative sign, the estimates are generally insignificant.

Kamakura and Balasubramanian (1988) extend the models of external, internal and mixed influence diffusion by considering a dynamic potential market and incorporating price explicitly in the model. Kamakura and Balasubramanian (1987) decompose total sales data into adoption and replacement sales, using only the adoption sales to analyze the diffusion of new durables. They assume two specifications for the dynamic potential market. One specification is the same as they use in their previous study and the other assumes that

$$M(t) = \delta_1 HH(t) \tag{2.38}$$

where $HH(t)$ is the number of electrified homes at time t and δ_1 is a constant. They test their models on six consumer durables and the results show that price does not affect the potential market.

Horsky (1990) extends the mixed influence model by considering a dynamic potential market. He proposes the following expression for the dynamic potential market:

$$M(t) = \delta_1 HH(t) \frac{1}{1+e^{-[\delta_2 + I(t) - \delta_3 P(t)]/ID(t)}} \tag{2.39}$$

where $HH(t)$ is the number of households at time t, $I(t)$ the average income at time t, $ID(t)$ the income dispersion at time t, $P(t)$ the average price at time t and δ_1, δ_2 and δ_3 are constants to be estimated. Data from four consumer durables (black and white televisions, color televisions, dishwashers and clothes dryers) are used for the empirical application. The results confirm that income and price are needed to explain sales for the analyzed durables.

Jain and Rao (1990) extend the Bass model to find the best way of incorporating price into a diffusion model. In one of their three specifications, the potential market is a function of price:

$$M(t) = MP(t)^{-\delta} \tag{2.40}$$

where $P(t)$ is the price at time t, δ the price elasticity of the potential market and M is a constant. Jain and Rao test their models with four consumer durables: room air conditioners, clothes dryers, color televisions and can openers. Their results show that price has no significant effect on can openers but affects the adoption rate of the other durables. (We address this model again in Chapter 5).

Bhargava, Bhargava and Jain (1991) extend the Bass model by incorporating price. They present four models incorporating price. Two of these models consider a dynamic potential market in the following way:

Model 1 $$M(t) = M\left[\frac{P(t)}{P(0)}\right]^{\delta_1} \tag{2.41}$$

Model 2 $$M(t) = M \exp\left[\delta_2\left(1 - \frac{P(t)}{P(0)}\right)\right] \tag{2.42}$$

where $P(t)$ is the inflation-adjusted price at time t, $P(0)$ the initial price at time t=0, and M, δ_1 and δ_2 are parameters. Bhargava, Bhargava and Jain (1991) do not find conclusive results regarding price when they analyze the diffusion of color televisions in India.

Jones and Ritz (1991) propose a system of diffusion models where the size of the potential market is affected by distribution (i.e. retailers that have adopted the new product). They represent the intermediary diffusion process with a modified Bass model and the consumer diffusion process with a constant transfer rate. They assume the following dynamic potential market:

$$M(t) = \delta D(t) \tag{2.43}$$

where $D(t)$ is the number of retailers at time t and δ is a constant. Their model is tested on movies and shows a good level of fit.

Parker (1992, 1993) extends the mixed influence diffusion model by considering a dynamic potential market. He uses one of the functions proposed by Kamakura and Balasubramanian (1988) (Equation (2.38)) for the dynamic potential market. He analyzes sixteen and nineteen durable product categories in his first and second paper, respectively. His results show that there is no single dominant specification in modeling the diffusion process for all the products.

Martins and Nascimento (1993) extend the diffusion model of external influence by allowing potential market to vary as a function of the market price. They do not specify any functional form. The authors do not present an empirical application, although they develop a graphical analysis using phase diagrams.

Bass, Krishnan and Jain (1994) propose the Generalized Bass Model. They consider fixed and dynamic potential markets. They specify the dynamic potential market as:

$$M(t) = MP(t)^{-\delta} \tag{2.44}$$

where $P(t)$ is price at time t, and δ and M are constants to be estimated. They test their model with three consumer durables (room air conditioners, clothes dryers and color televisions). Their results show that, in almost every instance, the estimates of δ are not significant or have the wrong sign. (We address this model again in Chapter 4).

Mesak and Berg (1995) extend the mixed influence model by assuming a dynamic potential market. They use the function proposed by Kalish and Lilien (1986a, 1986b) for the dynamic potential market (Equation (2.35)). Nine consumer durables are considered in the empirical application and their results confirm that price affects the potential market.

Mesak (1996) extends the mixed influence diffusion model by proposing that marketing variables (price, advertising and distribution) can affect external influence, internal influence and/or the potential market. He tests some alternatives for the dynamic potential market (see Table 2.2). Mesak finds that distribution, but neither price nor advertising, affects the potential market.

Bottomley and Fildes (1998) extend the diffusion models of external, internal and mixed influence by incorporating price and by assuming a dynamic potential market. They use the same two options for the dynamic potential market as Kamakura and Balasubramanian (1988), given that they analyze the same kind of durables. They provide an empirical study on twelve consumer durable categories, six from the United Kingdom and six from the United States of America. Their results show that the model in which price affects the adoption rate is more accurate than that in which price affects the potential market.

Table 2.2.
Models assuming a dynamic potential market

Reference	Extended model	Innovation context	$M(t)$
Dodson and Muller (1978)	Mixed influence	Durable consumer and non-durable consumer products (no empirical application)	$M(t)=f(advertising)$
Mahajan and Peterson (1978)	Mixed influence	Durable consumer products (washing machines) and other “innovation” (United Nations membership)	$M(t)=\delta_1+\delta_2 HH(t)$ $HH(t)$: the number of housing starts in the United States at time t –for washing machines- (or number of countries in the world at time t –for United Nations membership-), δ_1 and δ_2 (rate of increase in the potential market) are constants
Mahajan, Peterson, Jain and Malhotra (1979)	Mixed influence	Durable consumer products (gas rangers, washing machines and gas water heaters)	$M(t)=\delta_1+\delta_2 HH(t)$ $HH(t)$: number of housing starts in the United States at time t for washing machines, δ_1 and δ_2 (rate of increase in the potential market) are constants
Sharif and Ramanathan (1981)		Frequently purchased consumer products (oral contraceptive) Community innovation (fluoridated water usage) Firm innovation (credit-card banking)	Alternatives for $M(t)$: $M(t)=M_0 e^{\delta_1 t}$ $M(t)=M_0(1+\delta_2 t)$ $M(t)=\dfrac{\delta_3}{1+\delta_4 e^{-\delta_5 t}}$ $M(t)=\delta_3 - \delta_7 e^{-\delta_8 t}$ M_0: potential market at the time of product introduction ($M_0>0$), δ_1, δ_2, δ_3, δ_4, δ_5, δ_6, δ_7 and δ_8 are positive constants
Feichtinger (1982)	Mixed influence	New product (unspecified product) (Phase diagram)	$M(t)=f(price)$

Table 2.2.
Models assuming a dynamic potential market (continued)

Reference	Extended model	Innovation context	$M(t)$
Jorgensen (1983)	Mixed influence	Durable consumer products (no empirical application)	$M(t) = \delta_1 + \delta_2 P(t)$ $P(t)$: price at time t, $\delta_1>0$ and $\delta_2<0$ are constants
De Palma, Droesbeke and Lefevre (1984)	Mixed influence	Durable consumer products (no empirical application)	Alternatives for $M(t)$: $M(t) = f(P(t))$ $M(t) = M + \left(\frac{\delta_1}{P(t)}\right)^{\delta_2}$ $P(t)$: price at time t, M: potential market, δ_1 and δ_2 (price effect "power") are constants
Kalish (1985)	Mixed influence	Durable products (unspecified)	$M(t) = f\left(\frac{P(t)}{U(N(t)/M_0)}\right)$ where $f(P(t)) = M_0 e^{-\delta_1 P(t)}$ and $U\left(\frac{N(t)}{M_0}\right) = \frac{\delta_2 + \left(\frac{N(t)}{M_0}\right)^2}{\delta_2 + 1}$ $P(t)$: price at time t, $U(t)$: uncertainty at time t, M_0: potential market at zero price or at time t=0, δ_1 and δ_2 are constants
Olson and Choi (1985)	Mixed influence	Durable consumer products (black and white televisions, color televisions, clothes dryers and dishwashers)	$M(t) = M_0 e^{\delta t}$ M_0: potential market at the time of product introduction (M_0>0), δ: growth rate of potential market (it is exogenously determined and known)
Kalish and Lilien (1986a, 1986b)	Mixed influence	Durable consumer products (photovoltaic system)	$M(t) = M_0 e^{-\delta P(t)}$ $P(t)$: price at time t M_0: potential market at the time of product introduction (M_0>0), δ is a constant

Table 2.2.
Models assuming a dynamic potential market (continued)

Reference	Extended model	Innovation context	$M(t)$
Bayus (1987)	Mixed Influence	Durable consumer products (compact disc)	$M(t) = \sum_{j=1}^{J} HH(t) SEG_j(t) AWARE_j(t)$. $HH(t)$: total number of households at time t, $SEG_j(t)$: proportion of $HH(t)$ that is segment j at time t, $AWARE_j(t)$: proportion of segment j that is aware of the product at time t, $INTENT_j(t)$: proportion of segment j that is aware of the product and has appositive purchase intentions at time t, J: number of segments
Kamakura and Balasubramanian (1987)	Mixed influence	Durable consumer products (refrigerators, vacuum cleaners, toasters and electric blankets)	$M(t) = \delta_1 HH(t) P(t)^{\delta_2}$ $HH(t)$: number of electrified homes at time t. $P(t)$: price index at time t, δ_1 (final penetration or proportion of the total number of homes expected to adopt the product, if price was kept at its original level) and δ_2 are constants
Kamakura and Balasubramanian (1988)	External, Internal and Mixed influence	Durable consumer products (air conditioners, refrigerators, vacuum cleaners, toasters, blenders and mixers)	Alternatives for $M(t)$: $M(t) = \delta_1 HH(t) P(t)^{\delta_2}$ $M(t) = \delta_1 HH(t)$ $HH(t)$: number of electrified homes at time t, $P(t)$: price index at time t, δ_1 (or the final penetration level) and δ_2 are constants
Horsky (1990)	Mixed influence	Durable consumer products (black and white TVs, color TVs, dishwashers and clothes dryers)	$M(t) = \dfrac{\delta_1 HH(t)}{1 + \exp\left(\dfrac{-(\delta_2 + I(t) - \delta_3 P(t))}{ID(t)}\right)}$ $HH(t)$: number of households at time t, $I(t)$: average wage at time t, $ID(t)$: wage dispersion at time t, $P(t)$: average price at time t, δ_1, δ_2 and δ_3 are constants
Jain and Rao (1990)	Mixed influence	Durable consumer products (black and white TVs, color TVs, dishwashers and clothes dryers)	$M(t) = MP(t)^{-\delta}$ $P(t)$: price at time t, M and δ (price elasticity of potential market) are constants

Table 2.2.
Models assuming a dynamic potential market (continued)

Reference	Extended model	Innovation context	$M(t)$
Bhargava, Bhargava and Jain (1991)	Mixed influence	Durable consumer products (color TVs)	$M(t) = M\left(\frac{P(t)}{P(0)}\right)^{\delta_1}$ $M(t) = M \exp\left[\delta_2\left(1 - \frac{P(t)}{P(0)}\right)\right]$ $P(t)$: inflation-adjusted price at time t, $P(0)$: initial price at time t=0, M, δ_1 and δ_2 are parameters.
Jones and Ritz (1991)	Mixed influence (equation system)	"Durable" consumer products (movies)	$M(t) = \delta D(t)$ $D(t)$: number of retailers at time t, δ is a constant
Parker (1992)	Mixed influence	Consumer durable technological products (bed covers, blenders, calculators, clothes dryers, dishwashers, disposers, freezers, irons, microwave ovens, ranges, built-in ranges, refrigerators, room air conditioners, steam irons, color TVs, black and white TVs, and water pulsators)	$M(t) = \delta HH(t)$ $HH(t)$: number of households wired with electricity at time t, δ: measures the final household penetration level of ($0<\delta\leq 1$)
Martins and Nascimento (1993)	External, influence	Non-durable products (no empirical application)	$M(t) = f(P(t))$ $P(t)$: price at time t
Parker (1993)	Mixed influence	Consumer durable technological products (bed covers, blenders, calculators, clothes dryers, dishwashers, disposers, freezers, irons, microwave ovens, ranges, built-in ranges, refrigerators, room air conditioners, steam irons, color TVs, black and white TVs, water pulsators, washers and vacuums)	$M(t) = \delta HH(t)$ $HH(t)$: number of households wired with electricity at time t, δ: measures the final household penetration level of ($0<\delta\leq 1$)
Bass, Krishnan and Jain (1994)	Mixed influence	Durable consumer goods (room air conditioners, color TVs and clothes dryers)	$M(t) = MP(t)^{-\delta}$ $P(t)$: price at time t, M and δ are constants
Mesak and Berg (1995)	External, Internal and Mixed influence	Consumer durable technological products (dishwashers, electric dryers, disposers, color TVs, refrigerators, freezers, ranges, black and white TVs, air conditioners)	$M(t) = Me^{-\delta P(t)}$ $P(t)$: real (deflated) price index for the product at time t, M and δ are constants

Table 2.2.
Models assuming a dynamic potential market (continued)

Reference	Extended model	Innovation context	$M(t)$
Mesak (1996)	Mixed influence	Durable consumer products (Cable TV)	Alternatives for $M(t)$: $M(t) = Mf_3$ $M(t) = Mf_2 f_3$ $M(t) = Mf_1 f_3$ $M(t) = Mf_1 f_2 f_3$ $M(t) = M(f_2 + \delta_1 f_3)$ $M(t) = M(f_1 + \delta_2 f_3)$ $M(t) = M(f_1 + \delta_3 f_2 + \delta_4 f_3)$ where $f_1(P(t)) = P(t)^{-\delta}$, $\delta>1$ $f_2(A(t)) = \sqrt{A(t)}$ $f_3(D(t)) = D(t)$ $P(t)$: real (deflated) price index for the average monthly basic rate at time t, $A(t)$: real (deflated) index of advertising expenditures at time t, $D(t)$: distribution index at time t, δ_1, δ_2 and δ_3 are constants
Bottomley and Fildes (1998)	External, Internal and Mixed influence	Consumer durable technological products (color TVs, video cassette recorders, microwave ovens, video-cameras (inc. camcorders), compact disc players – in UK-) (air conditioners, refrigerators, vacuum cleaners, blenders, mixers and toasters – in the USA-)	Alternatives for $M(t)$: $M(t) = \delta_1 HH(t) P(t)^{\delta_2}$ $M(t) = \delta_1 HH(t)$ $HH(t)$: number of electrified homes at time t, $P(t)$: price index at time t, δ_1 (or the final penetration level, $0<\delta_1\leq 1$) and δ_2 are constants

The extensions of the basic diffusion model showed in this section reveal the importance of assuming a dynamic potential market. Price and/or the number of households are the variables mostly used to influence the potential market. Price has received the most attention due to its critical role in influencing the demand for a product (Kalish and Sen, 1986). The choice of the number of households (electrified homes) as a relevant variable is appropriate given that the majority of studies address the diffusion of electrical durables. The choice of the appropriate variable(s) is crucial in modeling the dynamic potential market accurately. However, this choice is not always easy. Bass, Krishnan and Jain (1994, p. 218) point out that "*it is probably best* *to treat M as fixed because guesses about a fixed M are probably intuitively more feasible than guesses about the influence of decision variables on M*".

2.4.2.3. Assumption 3. The parameters of external and internal influence do not change

The external influence diffusion model assumes that the diffusion process of an innovation is due exclusively to sources other than interpersonal communication and that the effect of these sources (denoted by β_1) is the same for any potential adopter, regardless of their characteristics and the time of adoption.

The internal influence model, which only considers the existence of personal communication between members of the social system -$(N(t)/M)[M\text{-}N(t)]$-, also establishes that the effect of interaction between previous and potential adopters (denoted by β_2) is fixed or constant over time[23].

The mixed influence model also assumes stability in their parameters during the diffusion process.

Some authors consider the case where the parameters of external and internal influence change over time and represent them as functions of factors that affect the diffusion process of the innovation: $\beta_1(t)=f(V(t))$ and $\beta_2(t)=f(V(t))$, where $V(t)$ is a vector of potentially important factors in the diffusion process, $f(.)$ is the functional shape of this influence (the functional shape can be equal or different for $\beta_1(t)$ and $\beta_1(t)$), $\beta_1(t)$ is a function that expresses external influence (time-varying external influence parameter) and $\beta_2(t)$ is a function that expresses internal influence (time-varying internal influence parameter). The authors introduce the time-varying diffusion parameters into the diffusion model in different ways. Putsis (1998), quoting Sarris (1973) and Judge, Griffiths, Hill, Lütkepohl and Lee (1985), points out that aggregation, proxy variables, non-linearity, and omitted variables can result in varying parameters.

[23] Given that $N(t)\left[M-N(t)\right]=\sum_{j=1}^{t} n(j)\left[M-N(t)\right]$, it is easy to see that it is implicitly assumed that the effect of interaction between previous and potential adopters is identical, regardless of time of adoption or interaction. Therefore, internal influence represented by $n(1)[M\text{-}N(t)]$ is equivalent to that represented by $n(t)[M\text{-}N(t)]$ (Mahajan and Peterson, 1985).

Table 2.3.
Time-varying diffusion parameters in diffusion models

Diffusion model of external influence

$$n(t) = \frac{dN(t)}{dt} = \beta_1(t)\left[M - N(t)\right]$$

Diffusion model of internal influence(*)

$$n(t) = \frac{dN(t)}{dt} = \beta_2(t)\frac{N(t)}{M}\left[M - N(t)\right]$$

Mixed influence diffusion model(*)

… using a non-separable function of the diffusion process

$$n(t) = \frac{dN(t)}{dt} = \left(\beta_1(t) + \beta_2\frac{N(t)}{M}\right)\left[M - N(t)\right]$$

$$n(t) = \frac{dN(t)}{dt} = \left(\beta_1 + \beta_2(t)\frac{N(t)}{M}\right)\left[M - N(t)\right] \quad \text{or}$$

$$n(t) = \frac{dN(t)}{dt} = \left(\beta_1(t) + \beta_2(t)\frac{N(t)}{M}\right)\left[M - N(t)\right]$$

… using a separable function of the diffusion process

$$n(t) = \frac{dN(t)}{dt} = \left(\beta_1 + \beta_2\frac{N(t)}{M}\right)f(V(t))\left[M - N(t)\right]$$

where

$n(t)=dN(t)/dt$: non-cumulative number of adopters at time t or the rate of diffusion at time t
$N(t)$: cumulative number of adopters at time t
M: potential market or population of potential adopters
$\beta_1(t)$: time-varying parameter of external influence
$\beta_2(t)$: time-varying parameter of internal influence
β_1: parameter of external influence
β_2: parameter of internal influence
$V(t)$: key factors at time t
$f(.)$: functional shape of the influence of key factors ($V(t)$)

(*): Internal influence is represented by $bN(t)$ instead of $\beta_2(N(t)/M)$ if the Mahajan and Peterson (1985) specification is used.

Easingwood, Mahajan and Muller (1981) develop the Non-Symmetric Responding Logistic model (NSRL). Their model assumes that the word-of-mouth effect on potential adopters is flexible and may increase, decrease or remain constant over time:

$$\beta_2(t) = \beta_2 \left(\frac{N(t)}{M} \right)^{\delta} \tag{2.45}$$

where *N(t)* is the non-cumulative number of adopters at time *t*, *M* the potential market and δ is the parameter of non-uniform influence. Hence, their diffusion model with varying internal influence is:

$$n(t) = \beta_2 \left(\frac{N(t)}{M} \right)^{\delta+1} \left[M - N(t) \right]. \tag{2.46}$$

The authors illustrate their model using data from four medical innovations. The results show that their model fits the data very well. (This model is discussed in more detail in Chapter 5).

Lilien, Rao and Kalish (1981), extending the mixed influence diffusion model, propose a trial-repeat diffusion model with promotional efforts. They propose the following diffusion model:

$$\begin{aligned} S(t) = {} & \left[\delta_{11} X(t-1) + \delta_{12} X(t-1)^2 \right] \left[M - S(t-1) \right] + \\ & \delta_2 \left[S(t-1) - S(t-2) \right] \left[M - S(t-1) \right] + \\ & \left[1 - \delta_3 X_c(t-1) \right] S(t-1) \end{aligned} \tag{2.47}$$

where *S*(t) is sales of the product in the time period t, M is total market sales, *X*(t) is detailing effort associated with the product in the time period t, $X_c(t)$ is detailing effort associated with competitor products in the time period t, and δ_{11}, δ_{12}, δ_2, and δ_3 are parameters to be estimated. They consider that the parameter of external influence depends on promotional efforts -detailing-. Their model is validated on two prescription drugs. The authors get significant, although small, estimates for detailing effectiveness. (This model is discussed in more detail in Chapter 6).

Easingwood, Mahajan and Muller (1983) develop the Non-Uniform Influence Innovation Diffusion model (NUI). This is a mixed influence model in which the parameter of internal influence systematically varies over time as a function of penetration level, as with their previous model (NSRL). The authors illustrate their model using data from five consumer durables. Their results show that their model fits the data very well. (This model is discussed in more detail in Chapter 5).

Horsky and Simon (1983) extend the mixed influence model by incorporating advertising. In their model, advertising affects external but not internal influence. Their model is tested with telephone banking. Their results show that advertising affects the diffusion process in the five cities where the new system was introduced.

Teng and Thompson (1983) and Thompson and Teng (1984), working on policy questions involving introductions of new products, extend the mixed influence diffusion model by introducing advertising. Advertising is incorporated following the Nerlove-Arrow (1962) and Ozga (1960) advertising models. Their models allow the parameters of external and internal influence to be linear functions of advertising. Specifically, they propose:

$$n(t) = \left[a + \delta_1 A(t) + \left(b + \delta_2 A(t)\right) N(t)\right]\left[M - N(t)\right] \tag{2.48}$$

where a and b are similar to the terms in the Mahajan and Peterson (1985) specification, $\delta_1 A(t)(M\text{-}N(t))$, which represents the effect of advertising on innovators, is similar to the corresponding term in the Vidale-Wolfe (1957) model, and $\delta_2 A(t)(N(t))(M\text{-}N(t))$, which represents the effect of advertising on imitators, is similar to the corresponding term in Ozga's (1960) advertising model. The analytical complexity makes numerical experiments a useful way to show how their models work.

Kalish (1985) proposes a model divided into two stages based on how a new product is perceived. The first is awareness, which depends on cumulative sales of the product, initial potential market, advertising and the information that potential adopters have about the new product. The second is adoption, which depends on cumulative sales of the product, initial potential market, information that potential adopters have about the new product and price. Kalish tests his model on an unspecified durable good, but he only uses the adoption part of this model since awareness data is not available. His results show that his model provides good fit to the data.

Srivastava, Mahajan, Ramaswami and Cherian (1985) develop a multi-attribute diffusion model for forecasting the acceptance of potential investment alternatives for consumers. They extend the mixed influence diffusion model by considering that external and internal influences are functions of relevant innovation attributes. Although they consider five attributes, only two (perceived likelihood of negative return and perceived information cost) of them are considered in their empirical analysis. Their multi-attribute diffusion model considers the following time-varying parameters of external and internal influence:

$$a(t) = \left[IC(t)^{\delta_1}\, LLP(t)^{\delta_2}\right]\delta_3 \tag{2.49}$$

$$b(t) = \left[IC(t)^{\delta_1}\, LLP(t)^{\delta_2}\right]\delta_4 + \delta_5 \tag{2.50}$$

where $IC(t)$ are the information costs at time t, $LLP(t)$ the likelihood of negative return at time t, and δ_1, δ_2, δ_3, δ_4 and δ_5 are constants. The results show that in twelve out of fourteen investment alternatives their model is better than the naïve model (i.e. a model without information about the innovation attributes) at predicting the diffusion patterns.

Eliashberg and Jeuland (1986) extend the external influence model by incorporating price. They propose two functions for external influence:

$$\text{monopoly period} \quad a_1(t) = \delta_1\left(1 - \delta_2 P_1(t)\right) \quad 0 \le t \le T_1 \tag{2.51}$$

duopoly period $a_i(t) = \delta_i\left(1 - \delta_2 P_i(t)\right) + \delta_3\left(P_j(t) - P_i(t)\right)$ i,j=1,2, $j \neq i$, $T_1 \leq t \leq T_2$ (2.52)

where $P_i(t)$ is the price of product i at time t, T_1 is the time of second entry, T_2 is the time horizon, δ_1 can be interpreted as overall marketing advantage, δ_2 reflects price sensitivity and δ_3 is the effect of the price differential between the two products. Several numerical simulations are provided by the authors.

Kalish and Lilien (1986a, 1986b) extend the mixed influence model by considering a dynamic potential market and incorporating internal influence as a perceived product-quality feedback term. They propose the following specification for word-of-mouth:

$$bN(t) = f(Q(t)) = b\sum_{j=1}^{t} PQ(j)S(j)\left(\frac{1}{1+\delta}\right)^{t-j} \tag{2.53}$$

where $Q(t)$ is the perceived product quality or reputation at time t, $PQ(t)$ the expected response of adopters to the performance of products adopted in period t, $S(t)$ the new adopters in the tth period (current sales level), b and δ (forgetting factor) are constants. Kalish and Lilien test their model on a new durable product (photovoltaic system). Kalish and Lilien compare their results with those of the Bass model for fit and predictive ability. Their model gives a higher corrected R^2 and smaller root mean squared error of prediction than the Bass model.

Simon and Sebastian (1987), extend the Bass model by considering that advertising can affect either external or internal influence. They extend the work of Horsky and Simon (1983). They propose several specifications to incorporate advertising into the diffusion model. They test their model with one product: telephones. They reject the idea that sales depend only on advertising efforts in a single period, which is consistent with the theoretical expectations. The Nerlove-Arrow (1962) advertising model shows the best results for choosing lags in advertising efforts. Their results show that, although advertising efforts affect both external and internal influence, the model that considers that advertising only affects internal influence is slightly superior.

Dockner and Jorgensen (1988a) propose a mixed influence diffusion model in which external and/or internal influence are affected by advertising. They incorporate advertising as a linear function into the diffusion model (using non-separable functions). They do not show any empirical application or numerical results.

Horsky and Mate (1988) extend the mixed influence diffusion model by incorporating advertising. They focus on optimal advertising policies. As in Horsky and Simon (1983), the authors specify the effectiveness of advertising as a logarithmic function of advertising expenditure. Managerial implications are shown through numerical evaluations.

Rao and Yamada (1988) provide support for the Lilien, Rao and Kalish (1981) model -Equation (2.47)- by analyzing twenty prescription drugs. Their results show that promotional activities affect the diffusion process, given that the detailing estimates generally present the expected signs and are significant.

Dockner and Jorgensen (1992) extend the mixed influence model by assuming that advertising affects external influence (following Horsky and Simon, 1983). The authors provide some analytical results.

Parker (1992) extends the mixed influence diffusion model by incorporating price as both a separable and non-separable function of the diffusion process. He considers the following specification for price: $f(P(t))=P(t)^{\delta(t)}$, where $P(t)$ is price and $\delta(t)$ represents price elasticity. Parker proposes several time-varying parameter formulations of $\delta(t)$. Furthermore, he considers the parameter of non-uniform influence introduced by Easingwood, Mahajan and Muller (1981, 1983). He analyzes sixteen durable product categories. His results show that there is no single dominant specification in modeling the diffusion process for all products.

Parker (1993) extends the mixed influence diffusion model (in fact the Bass model) by considering a heterogeneous adopter population, non-uniform internal influence and a dynamic potential market. He follows Jeuland (1981) by introducing a heterogeneous adopter population, and Easingwood, Mahajan and Muller (1981, 1983) in introducing non-uniform internal influence. He analyzes sixteen durable product categories. His results shows that diffusion processes are best captured by the mixed influence diffusion model with non-uniform internal influence and a dynamic potential market. (We address this model again in Chapter 5).

Hahn et al. (1994) extend the model of mixed influence diffusion by allowing for non-durable products and incorporating promotional efforts into the model. They consider that promotional efforts by the firm and its competitors affect external influence. They propose the following two specifications for external influence:

form 1 $$\beta_1(t) = \beta_1 + \delta \ln\left[\frac{X(t)}{X_c(t) + X(t)}\right] \tag{2.54}$$

form 2 $$\beta_1(t) = \beta_1 + \delta \ln\left[X(t)\right] \tag{2.55}$$

where $X(t)$ is detailing and journal advertising efforts associated with the product in t, $X_c(t)$ is detailing and advertising journal efforts associated with competitor products in t, and β_1 and δ are parameters to be estimated. Their model is validated on twenty-one prescription drugs in seven different product classes. Their results confirm that, in general terms, promotional efforts affect external influence. (This model is discussed in more detail in Chapter 6)

Parker and Gatignon (1994) address the impact of marketing variables (price and advertising) on the diffusion process of competing brands. The authors propose alternative specifications for brand–level first purchase diffusion models. Some of these specifications assume separable marketing effects (affecting the adoption rate) and others assume non-separable effects (affecting the parameter of external or internal influence). They propose the following response functions for marketing variables (price and advertising):

form 1 $$f_1(P(t),A(t)) = P(t)^{\delta_1+\delta_2 B(t)}\,A(t)^{\delta_3+\delta_4 B(t)} \tag{2.56}$$

form 2 $$f_2(P(t),A(t)) = PM(t)^{\delta_1+\delta_2 B(t)}\,AM(t)^{\delta_3+\delta_4 B(t)} \tag{2.57}$$

where $PM(t) = \dfrac{P(t)}{\left(1/B(t)\right)\sum_{j=1}^{B(t)} P_j(t)}$ and $AM(t) = \dfrac{A(t)}{\sum_{j=1}^{B(t)} A_j(t)}$, and where $P(t)$ is price at time t, $A(t)$ advertising at time t, $B(t)$ the number of competing brands in the product category at time t, and δ_1, δ_2, δ_3 and δ_4 are constants. These response functions can affect external or internal influence. They consider nine different brands in the hair styling mousses product category. Their results show that each brand is characterized by a different diffusion model. Although marketing variables are critical in the diffusion of brands, their impact is not identical across brands. Their results also show that the sensitivity of trials to price remains constant or increases over time, but advertising sensitivity can be insignificant, increase or decrease over time, depending on the order of entry.

Jain, Mahajan and Muller (1995) extend the Bass model by assuming that the number of samples available in the marketplace before introducing a new product affects its diffusion process. During this time, the new product is in a monopolistic situation. They postulate that product sampling creates an important number of initial adopters who enhance the rate of adoption of the new product. They incorporate sampling's effect on the parameter of external influence following Horsky and Simon (1983) when they incorporate advertising into a diffusion model:

$$\beta_1(t) = \beta_1 + \delta \log\left(1 + PS_0\right) \tag{2.58}$$

where PS_0 is the product sampling level, δ measures the impact of sampling on the parameter of external influence, and β_1 is another parameter that equals the parameter of external influence of the basic mixed influence diffusion model when the product sampling level is zero. The authors study durable and non-durable products through a numerical analysis. They find that, whereas a high sampling level is appropriate for products with a high parameter of internal influence, it is not for those products with a high parameter of external influence.

Mesak and Berg (1995) propose alternative diffusion models that incorporate price and replacement purchases. Some of their models incorporate price as a non-separable function affecting external influence, internal influence (see Table 2.3) or the potential market. Nine durable consumer products are considered in the empirical application. Their results show that, for the first purchase model and for high-priced consumer durables, price is likely to affect the potential market.

Mesak (1996) proposes a general mixed influence diffusion model that incorporates marketing variables (price, advertising and distribution). Mesak considers that price and advertising can affect external and/or internal influence using both separable and non-separable functions. He proposes alternatives for time-varying external and internal influence parameters (see Table 2.3). Mesak finds that price affects external influence, and advertising affects diffusion rate.

Putsis (1998) extends the mixed influence model. He proposes a flexible diffusion model with varying parameters that includes marketing variables (i.e. price) and replacement sales. His model is validated using data for two consumer durables (color televisions and videocassette recorders). His results suggest that the price parameter varies over time, and stochastic parameter specifications produce a substantially better fit.

Swami and Khairnar (2003) extend the Bass model to situations of limited availability and expiration date. In their model the previous situations are proposed to affect the consumers' innovation and imitation rates, and consequently, their propensity to purchase the product at any time. Hence, innovation and imitation parameters are both time-dependent. Swami and Khairnar use data for eight concerts of the Vancouver Symphony Orchestra in Vancouver, British Columbia, Canada. Their results show that their model can provide significant improvement in prediction of products characterized by the scarcity effects.

Table 2.4 summarizes previous studies that assume time-varying parameters of external and/or internal influence.

Table 2.4.
Models assuming dynamic parameters of external and/or internal influence.

Reference	Extended model	Innovation context	$\beta_1(t)$ / $a(t)$ (*)	$\beta_2(t)$ / $b(t)$ (*)
Easingwood, Mahajan and Muller (1981)	Internal influence	Medical innovations (Ultrasound, CT head scanner, CT body scanner and mammography)		$\beta_2(t)=\beta_2\left(\frac{N(t)}{M}\right)^{\delta}$ $N(t)$: non-cumulative number of adopters at time t, M: potential market, β_2 and δ are constants
Lilien, Rao and Kalish (1981)	Mixed influence	Frequently purchased consumer products (prescription drugs)	$a(t)=\delta_{11}X(t-1)+\delta_{12}X(t-1)^2$ $X(t)$: detailing at time t, δ_{11} and δ_{12} are constants	
Easingwood, Mahajan and Muller (1983)	Mixed influence	Durable consumer products (black and white TVs, color TVs, clothes dryers, room air conditioners and dishwashers)		$\beta_2(t)=\beta_2\left(\frac{N(t)}{M}\right)^{\delta}$ $N(t)$: non-cumulative number of adopters at time t, M: potential market, β_2 and δ are constants
Horsky and Simon (1983)	Mixed influence	"Durable" products (telephone banking as a new system)	$a(t)=a+\delta\ln(A(t))$ $A(t)$: advertising at time t, a and δ are constants	
Teng and Thompson (1983)	Mixed influence	Durable products (numerical solutions of a number of examples)	$a(t)=a+\delta\ln(A(t))$ $A(t)$: advertising at time t, a and δ are constants	$b(t)=b+\delta\ln(A(t))$ $A(t)$: advertising at time t, b and δ are constants
Thompson and Teng (1984)	Mixed influence	Durable products (numerical solutions of a number of examples)	$a(t)=a+\delta\ln(A(t))$ $A(t)$: advertising at time t, a and δ are constants	$b(t)=b+\delta\ln(A(t))$ $A(t)$: advertising at time t, b and δ are constants
Kalish (1985)	Mixed influence	Durable products (unspecified)	$a(t)=f(A(t))$ $A(t)$: advertising at time t	

Table 2.4.
Models assuming dynamic parameters of external and/or internal influence (continued).

Reference	Extended model	Innovation context	$\beta_1(t)$ / $a(t)$ (*)	$\beta_2(t)$ / $b(t)$ (*)
Srivastava, Mahajan, Ranaswami and Cherian (1985)	Mixed influence	Investment alternatives for consumers	$a(t)=\left[IC(t)^{\delta_1}\,LLP(t)^{\delta_2}\right]\delta_3$ $IC(t)$: information costs at time t, $LLP(t)$: likelihood of negative return at time t, δ_1, δ_2 and δ_3 are constants.	$b(t)=\left[IC(t)^{\delta_1}\,LLP(t)^{\delta_2}\right]\delta_4+\delta_5$ $IC(t)$: information costs at time t, $LLP(t)$: likelihood of negative return at time t, δ_1, δ_2, δ_4 and δ_5 are constants.
Eliashberg and Jeuland (1986)	External influence	Durable products (numerical simulations)	monopoly period: $a_1(t)=\delta_1\left(1-\delta_2 P_1(t)\right)$ $0\le t\le T_1$ duopoly period: $a_i(t)=\delta_i\left(1-\delta_2 P_i(t)\right)+\delta_3\left(P_j(t)-P_i(t)\right)$ $I,j=1,2, j\neq I$, $T_1\le t\le T_2$ $P_i(t)$: price of product I at time t, T_1: time of second entry, T_2: time horizon, δ_1, δ_2 and δ_3 are constants	
Kalish and Lilien (1986a, 1986b)	Mixed influence	Durable consumer product (photovoltaic system)		$bN(t)=b\sum_{j=1}^{t} PQ(j)S(j)\left(\frac{1}{1+\delta}\right)^{t-j}$ $Q(t)$: perceived product quality or reputation at time t, $PQ(t)$: expected response of adopters to the performance of products adopted in period t, $S(t)$: current sales level at time t, b and δ are constants
Simon and Sebastian (1987)	Mixed influence	Durable technological products (telephones)	$\beta_1(t)=\beta_1-\delta_1 f(A(t))$ where $f(A(t))$ can be: $f(A(t))=\delta_2\ln(A(t-\tau))$ $f(A(t))=\sum_{\tau=0}^{T}\delta_{2\tau}\ln(A(t-\tau))$ $f(A(t))=\delta_2\ln(G(t))$ where $G(t)=\sum_{\tau=0}^{T}\delta_{3\tau}A(t-\tau)$ $A(t)$: advertising at time t, β_1, δ_1, δ_2 and δ_3 are constants	$\beta_2(t)=\beta_2-\delta_1 f(A(t))$ where $f(A(t))$ can be: $f(A(t))=\delta_2\ln(A(t-\tau))$ $f(A(t))=\sum_{\tau=0}^{T}\delta_{2\tau}\ln(A(t-\tau))$ $f(A(t))=\delta_2\ln(G(t))$ where $G(t)=\sum_{\tau=0}^{T}\delta_{3\tau}A(t-\tau)$ $A(t)$: advertising at time t, β_1, δ_1, δ_2 and δ_3 are constants

Table 2.4.
Models assuming dynamic parameters of external and/or internal influence (continued).

Reference	Extended model	Innovation context	$\beta_1(t)$ / $a(t)$ (*)	$\beta_2(t)$ / $b(t)$ (*)
Dockner and Jorgensen (1988a)	Mixed influence	Durable products (no empirical application)	$a(t) = a + \delta \ln(A(t))$ $A(t)$: advertising at time t, a and δ are constants	$b(t) = b + \delta \ln(A(t))$ $A(t)$: advertising at time t, a and δ are constants
Horsky and Mate (1988)	Mixed influence	Durable products (numerical results)	$a(t) = a + \delta \ln(A(t))$ $A(t)$: advertising at time t, a and δ are constants	
Rao and Yamada (1988)	Mixed influence	Frequently purchased consumer products (prescription drugs)	$a(t) = \delta_{11} X(t-1) + \delta_{12} X(t-1)^2$ $X(t)$: detailing at time t, δ_{11} and δ_{12} are constants	
Dockner and Jorgensen (1992)	Mixed influence	Durable products (analytical results)	$a(t) = a + \delta \ln(A(t))$ $A(t)$: advertising at time t, a and δ are constants	
Parker (1992)	Mixed influence	Consumer durable technological products (bed covers, blenders, calculators, clothes dryers, dishwashers, disposers, freezers, irons, microwave ovens, ranges, built-in ranges, refrigerators, room air conditioners, steam irons, color TVs, black and white TVs, and water pulsators)	$\beta_1(t) = \beta_1 P(t)^{\delta(t)}$ $P(t)$: price at time t, $\delta(t)$: price elasticity function dependent on the age of the product category -t-, β_1 is a constant	$\beta_2(t) = \beta_2 P(t)^{\delta_1(t)} \left[\frac{N(t)}{M}\right]^{\delta_2}$ $N(t)$: non-cumulative number of adopters at time t, M: potential market, $P(t)$: price at time t, $\delta_1(t)$: price elasticity function dependent on the age of the product category -t-, β_1 and δ_2 are constants

Table 2.4.
Models assuming dynamic parameters of external and/or internal influence (continued).

Reference	Extended model	Innovation context	$\beta_1(t)$ / $a(t)$ (*)	$\beta_2(t)$ / $b(t)$ (*)
Parker (1993)	Mixed influence	Consumer durable technological products (bed covers, blenders, calculators, clothes dryers, dishwashers, disposers, freezers, irons, microwave ovens, ranges, built-in ranges, refrigerators, room air conditioners, steam irons, color TVs, black and white TVs, water pulsators, washers and vacuums)		$\beta_2(t) = \beta_2 \left(\frac{N(t)}{M} \right)^{\delta}$ $N(t)$: non-cumulative number of adopters at time t, M: potential market, β_2 and δ are constants
Hahn, Park, Krishnamurthi and Zoltners (1994)	Mixed influence	Frequently purchased consumer products (prescription drugs)	form 1: $\beta_1(t) = \beta_1 + \delta \ln \left[\frac{X(t)}{X_c(t) + X(t)} \right]$ form 2: $\beta_1(t) = \beta_1 + \delta \ln \left(X(t) \right)$ $X(t)$: detailing and journal advertising efforts associated with the product at time t, $X_c(t)$: detailing and journal advertising efforts associated with competing products at time t, β_1 and δ are constants	

Table 2.4.
Models assuming dynamic parameters of external and/or internal influence (continued).

Reference	Extended model	Innovation context	$\beta_1(t)$ / $a(t)$ (*)	$\beta_2(t)$ / $b(t)$ (*)
Parker and Gatignon (1994)	Mixed influence	Frequently purchased consumer products (hair styling mousses)	form 1: $\beta_1(t)=\beta_1[P(t)^{\delta_1+\delta_2 B(t)} * A(t)^{\delta_3+\delta_4 B(t)}]$ form 2: $\beta_1(t)=\beta_1[PM(t)^{\delta_1+\delta_2 B(t)} * AM(t)^{\delta_3+\delta_4 B(t)}]$ $PM(t)=\frac{P(t)}{\left(1/B(t)\right)\sum_{j=1}^{B(t)} P_j(t)}$ $AM(t)=\frac{A(t)}{\sum_{j=1}^{B(t)} A_j(t)}$ $P(t)$: price at time t, $A(t)$: advertising at time t, $B(t)$: the number of competing brands in the product category at time t, β_1, δ_1, δ_2, δ_3 and δ_4 are constants	form 1: $\beta_2(t)=\beta_2[P(t)^{\delta_1+\delta_2 B(t)} * A(t)^{\delta_3+\delta_4 B(t)}]$ form 2: $\beta_2(t)=\beta_2[PM(t)^{\delta_1+\delta_2 B(t)} * AM(t)^{\delta_3+\delta_4 B(t)}]$ $PM(t)=\frac{P(t)}{\left(1/B(t)\right)\sum_{j=1}^{B(t)} P_j(t)}$ $AM(t)=\frac{A(t)}{\sum_{j=1}^{B(t)} A_j(t)}$ $P(t)$: price at time t, $A(t)$: advertising at time t, $B(t)$: the number of competing brands in the product category at time t, β_1, δ_1, δ_2, δ_3 and δ_4 are constants
Jain, Mahajan and Muller (1995)	Mixed influence	durable and non-durable products (numerical results)	$\beta_1(t)=\beta_1+\delta\log\left(1+PS_0\right)$ PS_0: the product sampling level, β_2 and δ are constants	
Mesak and Berg (1995)	External, Internal and Mixed influence	Consumer durable technological products (dishwashers, electric dryers, disposers, color TVs, refrigerators, freezers, ranges, black and white TVs, air conditioners)	$a(t)=ae^{-\delta P(t)}$ $P(t)$: price at time t, a and δ are constants	$b(t)=be^{-\delta P(t)}$ $P(t)$: price at time t, b and δ are constants

Table 2.4.
Models assuming dynamic parameters of external and/or internal influence (continued).

Reference	Extended model	Innovation context	$\beta_1(t)$ / $a(t)$ (*)	$\beta_2(t)$ / $b(t)$ (*)
Mesak (1996)	Mixed influence	Consumer durable technological products (cable TV)	Alternatives for $a(t)$: $a(t)=\delta_1 f_1$ $a(t)=\delta_2 f_2$ $a(t)=\delta_1 f_1+\delta_2 f_2$ where $f_1(P(t))=P(t)^{-\delta}$, δ>1 $f_2(A(t))=\sqrt{A(t)}$ $P(t)$: real (deflated) price index for the average monthly basic rate at time t, $A(t)$: real (deflated) index of advertising expenditures at time t, δ_1 and δ_2 are constants	Alternatives for $b(t)$: $b(t)=\delta_1 f_1$ $b(t)=\delta_2 f_2$ $b(t)=\delta_1 f_1+\delta_2 f_2$ where $f_1(P(t))=P(t)^{-\delta}$, δ>1 $f_2(A(t))=\sqrt{A(t)}$ $P(t)$: real (deflated) price index for the average monthly basic rate at time t, $A(t)$: real (deflated) index of advertising expenditures at time t, δ_1 and δ_2 are constants
Putsis (1998)	Mixed influence	Consumer durable technological products (color TVs, video cassette recorders)	$a(t)=f(t, price, income)$	$b(t)=f(time, price, income)$
Swami and Khairnar (2003)	Mixed influence	"Durable" consumer products (arts companies)	$\beta_1(t)=\delta_1+\delta_2\frac{1}{T}+$ $\delta_3\frac{N(t)}{K}+\delta_4\frac{t}{T}\frac{N(t)}{K}$ $N(t)\le K-\varepsilon_1<M$ and $t\le T-\varepsilon_2$ $N(t)$: cumulative sale till date, t/T: fraction of time to event deadline, $N(t)/K$: proportion of seats sold to capacity δ_1, δ_2, δ_3, δ_4 and K are constants	$\beta_2(t)=\delta_1+\delta_2\frac{1}{T}+$ $\delta_3\frac{N(t)}{K}+\delta_4\frac{t}{T}\frac{N(t)}{K}$ $N(t)\le K-\varepsilon_1<M$ and $t\le T-\varepsilon_2$ $N(t)$: cumulative sale till date, t/T: fraction of time to event deadline, $N(t)/K$: proportion of seats sold to capacity δ_1, δ_2, δ_3, δ_4 and K are constants

(*): $\beta_1(t)=a(t)$ and $\beta_2(t)(N(t)/M)$ is represented by $b(t)N(t)$ if the Mahajan and Peterson (1985) specification is used.

Furthermore, we have to add to this group (Table 2.4) those studies that consider that relevant variables, such price or advertising, affect both the diffusion rate and the effective potential market. In these studies, these variables are introduced into the mixed influence diffusion model as a separable function of the diffusion process (see Table 2.3). In this case, they consider that external and internal influences are equally affected. These authors, who we will refer to in Section 2.4.2.9 in detail, are Robinson and Lakhani (1975), Bass (1980), Dolan and Jeuland (1981), Bass and Bultez (1982), Jeuland and Dolan (1982), Kalish (1983), De Palma, Droesbeke, Lefevre (1984), Rao and Bass (1985), Dockner and Jorgensen (1988b), Kamakura and Balasubramanian (1988), Jain and Rao (1990), Bhargava, Bhargava and Jain (1991), Bass, Krishnan and Jain (1994), Bottomley and Fildes (1998) and Krishnan, Bass and Jain (1999).

The extensions of the basic diffusion models in this section reveal the importance to researchers of assuming dynamic diffusion parameters, which is key to a better understanding of the diffusion patterns of innovations. Marketing variables, specifically price and advertising, are the variables mainly chosen by researchers to introduce dynamics in the diffusion parameters -external and internal influence parameters-. Researchers include the effect of the relevant variables using a number of functional shapes. The results show that, for the majority, the extended models provide better fit to the data and better predictive ability. The results also show that a specific relevant variable does not always follow the same pattern; i.e. a specific variable may affect external but not internal influence in some situations and may affect both in others.

2.4.2.4. Assumption 4. Only one adoption per adopter is permitted

The fundamental diffusion model does not allow repeat purchases, replacement or multiple adoptions.

The assumption of only one adoption per adopter can be valid for some consumer durables. However, a large number of innovations are of a non-durable nature, meaning that an increase in the number of adopters during the diffusion process is a result of both first and repeat purchases. Furthermore, for a large number of durables replacement and multiple-units represent significant components of total sales.

Although the use of short term data is justified when there is both a need to predict the evolution of a product in a market with a short sales record available and a desire to avoid first sales (adoption data) being contaminated by subsequent sales (replacement data), there are reasons to support a long term analysis of the diffusion process (Kamakura and Balasubramanian, 1988):

i. a critical evaluation of the long term sales record of a product can reveal the influence of significant variables when they have an effect in the long run;
ii. the use of a small number of observations to estimate the parameters of the model produces instability in the diffusion parameters; and

iii. it avoids the criticism that suggests that most successful applications may be the result of "*a judicious choice of …… time frame for analyzing the data*" (Bernhardt and Mackenzie (1972, pp.187).

Several researchers have relaxed this assumption by allowing more than one adoption per adopting unit (repeated purchases, replacement and multiple-unit purchases). We divide their studies into two groups. The first group has focused on diffusion models for frequently purchased products and a second group on diffusion models for durable products. Both groups of authors have avoided the contamination of adoption data by incorporating repeat purchases, replacement or multiple-unit purchases in the diffusion model. This incorporation implies modeling both adoption types (first purchases from non-users, trials) and repeat purchases, replacement and multiple-unit purchases, taking into account the fact that the structural drivers of each kind of sales are different. Whereas replacement[24] can be due to either a unit failure or a discretionary replacement dependent on the perceived condition and obsolescence of a working unit (Bayus and Gupta, 1992), multiple-unit acquisition of a durable may be the result of a new usage situation[25] and not be correlated with the age of the product.

However, there are authors who prefer to use first purchase data (short series) to avoid the contamination of adoption data; in this case, assumption 4 is not relaxed.

One of the main problems that researchers have to solve, when they want to integrate first and subsequent purchases into diffusion models, is how to divide total sales. This is a big problem for researchers because separate information is not usually available (Ratchford, Balasubramanian and Kamakura, 2000).

We will now briefly discuss some of the studies that relax assumption 4. Table 2.5 shows these studies, specifying the durable or non-durable nature of the innovation, the extended diffusion model and the applications provided.

[24] See Antonides (1990) and Bayus (1991) for consumer replacement behavior.
[25] "*For example, consumers may require a smaller television for a bedroom, a four-wheel-drive car for weekend fun, or a smaller refrigerator for the beer*" (Steffens, 2003, p.902).

Table 2.5.
Models assuming multiple adoptions

	Extended model	Innovation context
Frequently purchased products (repeat purchases)		
Dodson and Muller (1978)	Mixed influence	No empirical application
Dolan and Jeuland (1981)	Mixed influence	No empirical application (simulation)
Lilien, Rao and Kalish (1981)	Mixed influence	Prescription drugs
Jeuland and Dolan (1982)	Mixed influence	No empirical application (simulation)
Mahajan and Muller (1982)	Mixed influence	No empirical application
Mahajan, Wind and Sharma (1983)	Mixed influence	Prescription drugs
Rao and Yamada (1988)	Mixed influence	Prescription drugs
Martins and Nascimento (1993)	External Influence	No empirical application (phase diagrams)
Hahn, Park, Krishnamurthi and Zolters (1994)	Mixed influence	Prescription drugs
Durable products (replacement)		
Dodson and Muller (1978)	Mixed influence	No empirical application
Lawrence and Lawton (1981)	Mixed influence	Durable consumer product (an example)
Olson and Choi (1985)	Mixed influence	Durable consumer products (black and white televisions, color televisions, clothes dryers and dishwashers)
Bayus (1987)	Mixed influence	Durable consumer products (compact disc)
Kamakura and Balasubramanian (1987)	Mixed influence	Durable consumer products (refrigerators, vacuum cleaners, toasters and electric blankets)
Mesak and Berg (1995)	External, Internal and Mixed influence	Durable consumer products (dishwashers, electric dryers, disposers, color TVs, refrigerators, freezers, ranges, black and white TVs, air conditioners)
Putsis (1998)	Mixed influence	Durable consumer products (color TV and video cassette recorders)
(multiple-unit ownership)		
Steffens (2003)	Mixed influence	Durable consumer products (color TV and automobiles)

Studies on frequently purchased products: repeat purchases

While trial is the key to success for a durable innovation, the success of a non-durable good also depends on repeat sales in a competitive or multibrand market environment. Some attempts have been made to capture repeat purchase patterns. Below, we show some authors concerned with this subject. Although some authors such as Midgley (1976) and Parker and Gatignon (1994) present empirical applications on non-durable products, they are not considered here given that they focus on first purchase data and do not consider repeat purchases in their models. Others, such as Kalish (1983, 1985), although taking into account the possibility of frequently purchased products, do not specify how to incorporate repeat purchases into the diffusion model. Finally, although some authors consider repeat purchases in their multi-state diffusion model, they do not show an empirical application (e.g. Dodson and Muller, (1978)).

Dolan and Jeuland (1981) focus on optimal pricing policies and consider two demand situations: one for non-durable goods and another for durable goods. Although they consider repeat purchases for non-durables, they do not consider replacement for durables. Regarding non-durable goods, they consider that

$$\frac{dS(t)}{dt} = \frac{dS_1(t)}{dt} + S_1(t)\left[\delta_1 e^{\delta_2 P(t)}\right] \tag{2.59}$$

where $dS(t)/dt$ represents sales rate, $dS_1(t)/dt$ refers to initial purchases, $S_1(t)\left[\delta_1 e^{\delta_2 P(t)}\right]$ refers to repeat purchases, $P(t)$ is price at time t, δ_1 reflects the frequency of repeat purchases and δ_2 reflects price sensitivity. The authors use simulations to validate their model.

Lilien, Rao and Kalish (1981), extending the mixed influence diffusion model, propose a trial-repeat diffusion model with promotional efforts (i.e. detailing). Their model (see assumption 3, Equation (2.47)) shows three terms. The first term on the right of the equation represents triers due to company promotional efforts, the second term represents triers due to the word-of-mouth effect and the third term represents repeaters as an expression that accounts for competitors' promotional efforts. Their model is validated on two prescription drugs. The authors, analyzing detailing expenditures, get significant although small estimates for detailing effectiveness. (This model is discussed in more detail in Chapter 6).

Jeuland and Dolan (1982), investigating the optimal strategic pricing of innovations, extend the mixed influence model by incorporating price as a separable function of the diffusion process and allowing for repeat buying:

$$\frac{dN_2(t)}{dt} = \left[\left(a + bN_1(t)\right)\left(M - N_1(t)\right) + \delta_1 N_1(t)\right]P(t)^{-\delta_2} \tag{2.60}$$

where $N_1(t)$ is the cumulative number of triers at time t, $N_2(t)$ is cumulative sales at time t (including both trial and repeat), M is the potential market, $P(t)$ is price at time t, and a, b, δ_1 and δ_2 are parameters to be estimated. Parameter δ_1 signifies the extent of repeat purchase activity. The authors use simulations to validate their model.

Mahajan and Muller (1982) propose a general multi-stage diffusion model. They assume that total population consists of four major groups representing "non-users", "unawares", "awares" and "adopters". Furthermore, they divide adopters into triers and second, third…*j*th repeaters. Although, the authors show a flow diagram for their model, they do not show the complex set of mathematical specifications of the flows of consumers from one group to another nor an empirical application.

Mahajan, Wind and Sharma (1983) extend the mixed influence diffusion model by allowing for non-durable products. Specifically, they extend the first-purchase non-uniform influence model proposed by Easingwood, Mahajan and Muller (1983) by allowing repeat purchases. They focus on the non-uniform nature of the word-of-mouth effect:

$$S(t) = \beta_1 \left[M - S(t-1) \right] + \beta_2 \left(\frac{S(t-1)}{M} \right)^{\delta_1} \left[M - S(t-1) \right] + \delta_2 S(t-1) \qquad (2.61)$$

where $S(t)$ is sales of the product in the time period t, M is total market sales, and β_1, β_2, δ_1 and δ_2 are parameters to be estimated. The first term on the right of the equation represents triers due to external influence (company promotional efforts among others), the second term represents triers due to the word-of-mouth effect (this term captures the influence of word-of-mouth over time) and the third term represents repeaters. The authors validate their model on one prescription drug. (This model is discussed in more detail in Chapter 6).

Rao and Yamada (1988) provide support for the Lilien, Rao and Kalish (1981) model -Equation (2.47)- by analyzing twenty prescription drugs. Their results show that promotional activities affect the diffusion process.

Martins and Nascimento (1993) propose a diffusion model that captures the essence of non-durables in a competitive environment. Their model is an extension of the external influence diffusion model that allows adopters not to buy in the following period. However, no explicit distinction is made between trial and repeat purchases. Their model can be expressed as:

$$n(t) = a\left[M(t) - N(t) \right] - \delta N(t) \qquad (2.62)$$

where the first term on the right side of the previous equation corresponds to the diffusion model of external influence with dynamic potential market and the second reflects a fraction, δ, of last period buyers who do not purchase the product again. Martins and Nascimento do not present an empirical application, they develop a graphic analysis using phase diagrams.

Hahn et al. (1994) extend the model of mixed influence diffusion by allowing for non-durable products and incorporating promotional efforts into the diffusion model. They consider that promotional efforts by the firm and its competitors affect external influence. They propose two specifications for their model:

Specification 1
$$S(t) = \left(\beta_1 + \delta_1 \ln\left(\frac{X(t)}{X_c(t) + X(t)}\right)\right)\left[M - Q(t-1)\right] + \beta_2 \frac{S(t-1)}{M}\left[M - Q(t-1)\right] + \delta_2 Q(t-1) \quad (2.63)$$

Specification 2
$$S(t) = \left(\beta_1 + \delta_1 \ln\left(X(t)\right)\right)\left[M - Q(t-1)\right] + \beta_2 \frac{S(t-1)}{M}\left[M - Q(t-1)\right] + \delta_2 Q(t-1) \quad (2.64)$$

$$Q(t) - Q(t-1) = S(t) + \delta_2 Q(t-1) \quad (2.65)$$

where $S(t)$ is sales of the product in period t, M is total market sales, $X(t)$ is detailing and journal advertising efforts associated with the product in period t, $X_c(t)$ is detailing and journal advertising efforts associated with competing products in period t, and β_1, δ_1, β_2 and δ_2 are parameters to be estimated. The first term on the right side of both equations represents triers due to external influence; in specification 1 both company and competitor promotional efforts affect external influence whereas in specification 2 only company promotional efforts are considered. The second term represents triers due to the word-of-mouth effect and the third term represents repeaters. Their model is validated on twenty-one prescription drugs in seven different product classes. Their results show that, in general terms, promotional efforts affect external influence. (This model is discussed in more detail in Chapter 6).

Studies on durable products: replacement

We examine the literature that investigates both components of sales: first purchases and replacement. Hence, studies like that of Steffens (2001)[26], where first purchases are not analyzed, are not considered below[27]. The essential assumption behind most replacement models is that time for replacement (replacement age) can be represented by a "*probability distribution over the population of units in an analogous way to product failure*" (Steffens, 2003, p.903).

Dodson and Muller (1978) develop a multi-state diffusion model to forecast the sales of a durable good. They extend their initial model by allowing for the

[26] "*The first purchase component of sales is not considered since the current model makes no contribution in this area*" (Steffens, 2001, p.65)

[27] Neither do we consider studies like that of Bayus, Hong and Labe (1989), where the authors do not extend the fundamental diffusion model, because they follow a different approach.

replacement of durable products and for repeat purchases of frequently purchased products. However, the authors do not show an empirical application.

Lawrence and Lawton (1981), starting from the mixed influence diffusion model, discuss the simplest method of approximating the repurchases phenomenon. They simply assume that each piece of equipment has to be replaced in a certain number of years (the average life), and this produces a repeat of the original purchase curve shifted that number of years. So, adding both sales types (the original and the shifted curve), it is possible to produce the overall market sales forecast. This model assumes that the service life of the product is constant and known *a priori*. The authors provide a numerical example.

Olson and Choi (1985) extend the model of mixed influence diffusion by incorporating replacement and, as we discussed earlier, by considering a dynamic potential market. They introduce replacement into the model by adding replacement demand to the number of first-purchase buyers. Hence, the observed sales of the product in period t are:

$$S(t)= n(t)+r(t)+e(t) \tag{2.66}$$

$$r(t) = f\left(\mu, S^*(t-1)\right) \tag{2.67}$$

where $n(t) = \left(a + bN(t)\right)\left[M(t) - N(t)\right]$ is the number of first-purchase buyers at time t, $r(t)$ the replacement demand at time t, μ the mean of the product life, $S^*(t-1) = n(t-1) + r(t-1)$ a vector of observed sales from period 1 to period t-1, and $e(t)$ the error term of both components of sales. Olson and Choi (1985) employ the Rayleigh distribution to model replacement and recognize that product life is not constant but stochastic. Hence, this removes the restrictive assumption of the model developed by Lawrence and Lawton (1981). Their model is tested on four durable products (black and white televisions, color televisions, clothes dryers and dishwashers) and they compare their model with the logistic model. The results show that the logistic model betters their model with only one product (dishwashers).

Bayus (1987) studies contingent products; specifically captive products. Such products are unique in that the secondary product (e.g. software component) must be purchased for use with the primary product (e.g. hardware component). Bayus assumes that purchases of the primary product have long interpurchase times while those of the secondary product are of a repeat nature. Hence, software sales are obtained as a multiplicative function of hardware sales:

$$SWARE(t) = \sum_{j=1}^{J} \sum_{i=1}^{t} HWARE_j(i) S_j(t-i+1) \tag{2.68}$$

where $SWARE(t)$ is the software sales at time t, $HWARE_j(k)$ the hardware sales to segment j at time k, and $S_j(k)$ segment j's software purchase rate k time periods after the hardware was purchased. Bayus presents an application of his model in the compact disc prerecorded audio market. He points out that his results suggest that his model structure is a promising option for forecasting sales of new contingent products.

Kamakura and Balasubramanian (1987) extend the mixed influence diffusion model by incorporating price effects on the potential market and by allowing replacement. They incorporate replacement into the model in the following way:

$$S(t) = n(t) + r(t) + e(t) \tag{2.69}$$

$$r(t) = \sum_{i=1}^{t} \left[U(i-1) - U(i) \right] S(t-i) \tag{2.70}$$

where $S(t)$ are sales of the product at year t, $n(t) = \left(a + bN(t)\right)\left[M(t) - N(t)\right]$ the non-cumulative number of owners at year t, $r(t)$ the number of units that need to be replaced at year t, $U(i)$ the percentage of units that are expected to "survive" until i-years after purchase, and $e(t)$ is the random disturbance. Kamakura and Balasubramanian (1987) find that the Rayleigh distribution chosen by Olson and Choi (1985) does not capture replacement appropriately. Another difference among these authors is that the diffusion model developed by Kamakura and Balasubramanian (1987) assumes that the potential market depends on the number of electrified homes. The model is tested on four consumer durables. The results show that although the goodness of fit obtained with their model is not substantially better than with the simple diffusion model, its forecasting performance is clearly superior.

Mesak and Berg (1995) propose alternative diffusion models that incorporate price and replacement purchases. They assume that sales, $S(t)$, are given by:

$$S(t) = n(t) + r(t) \tag{2.71}$$

where $n(t)$ is the non-cumulative number of adopters at time t (first purchases from non-users) and $r(t)$ are replacement sales at time t (from users). The authors consider the three specifications of the fundamental diffusion model (external, internal and mixed influence) for $n(t)$, and combinations of these specifications and price. They propose two specifications for $r(t)$:

Specification 1 $$r(t) = \delta N(t) \tag{2.72}$$

Specification 2 $$r(t) = \delta_1 N(t) e^{-\delta_2 P(t)} \tag{2.73}$$

where $P(t)$ is price at time t, and δ, δ_1 and δ_2 are constants. Nine consumer durables are considered in the empirical application. Regarding replacement, their results show that: i) although first purchases can be price sensitive, replacement purchases may be either price sensitive or insensitive, and ii) pricing response functions are similar when first and repeat purchases are price sensitive.

Putsis (1998) extends the mixed influence model by proposing a flexible model with varying parameters and including marketing mix variables (i.e. price) and replacement sales. In contrast to other authors, like Olson and Choi (1985) or Kamakura and Balasubramanian (1987), Putsis proposes a formulation in which replacement purchases are not explicitly modeled; the parameters are already influenced by the age distribution of the existing stock. The model is validated using data for two consumer durables and the results suggest that the price parameter does in fact vary over time and that stochastic parameter specifications produce substantially better fits.

Within this group of authors concerned with incorporating replacement into diffusion models, we have to consider another group focused on the diffusion of successive generations (technological substitution). Fisher and Pry (1971) were pioneers in studying the demand relationship between one generation of a product and its successor; specifically they studied technological substitution. Other researchers have subsequently studied the diffusion of successive generations of products (e.g., Blackman, 1971; Peterka, 1977; Norton and Bass, 1987, 1992; Bayus, 1992; Bass, Krishnan and Jain, 1994; Speece and MacLachlan, 1995; Mahajan and Muller, 1996; Bass and Bass, 2001; Danaher, Hardie and Putsis, 2001). However, although it is important to recognize its existence, we are not going to enter into more detail due to the size of this area of research[28].

Studies on durable products: multiple-unit ownership

Very little attention has been given to multiple-unit ownership in diffusion modeling literature. Only two models have been detected, one developed by Bayus, Hong and Labe (1989) focuses on an age-based formulation and another developed by Steffens (2003) based on the Bass model. Given that the former treats the multiple units adoption process as an age-based process where the propensity to adopt an additional unit increases with the age of adopter's existing unit instead of following a diffusion-based approach[29], we do not consider this work here.

Steffens (2003) develops the following multiple-unit ownership diffusion model:

$$\frac{dNN_1(t)}{dt} = \left(a_1 + b_1 NN_1(t)\right)\left[\delta_1 N(t) - NN_1(t)\right] \tag{2.74}$$

where $NN_1(t)$ represent multiple-unit adopters, $\delta_1 N(t)$ the population of potential adopters of multiple units (specified as a proportion of those previously adopting a first unit δ_1), a_1 external influence on first multiple-unit adoptions and b_1 internal influence on first multiple-unit adoptions. Steffens assumes that the upper potential

[28] For a comprehensive review of technological substitution and successive product generations see Norton and Bass (1987), Kumar and Kumar (1992), Jiménez (1996) and Bayus, Kim and Shocker (2000).

[29] Within an aged-based process the variable influencing the hazard rate is the age of the existing unit whereas within a diffusion-based process two components are considered: a constant -product usage and external influence- and the number of earlier adoptions -internal influence- (Steffens, 2003).

of such adoptions is a fixed proportion δ_2 of multiple-unit adopters $NN(t)$. This leads to the following model for subsequent (two or more) multiple-unit adoptions $NN_2(t)$:

$$\frac{dNN_2(t)}{dt} = \left(a_2 + b_2 NN_1(t)\right)\left[\delta_2 NN_1(t) - NN_2(t)\right] \tag{2.75}$$

where a_2 represents external influence on subsequent multiple-unit adoptions and b_2 internal influence on subsequent multiple-unit adoptions. Steffens tests his model using color television and automotive industry data. The empirical results for both applications provide clear support for his model.

The studies in this section reveal the little attention devoted to the relaxation of assumption 4, which is probably due to the difficulties in accessing the required data. We have divided the studies into three groups. Firstly, in "studies on frequently purchased products: repeat purchases" we can differentiate one group of research that does not provide empirical applications and another group that does and is focused exclusively on prescription drugs. The latest study on diffusion of prescription drugs, developed by Hahn et al. (1994) (we address this study in detail in Chapter 6), represents an important improvement to the previous studies as the extended model shows superior parameter face validity, fit to the data and forecast ability. Although the prescription drugs group has opened a promising line of research that should be further addressed, there is a clear need to investigate other innovation types. Secondly, in "studies on durable products: replacement" there is no consensus on the best way to model replacement. At the moment, they are focused on consumer products. Thirdly, "studies on durable products: multiple-unit ownership" is an emerging group.

2.4.2.5. Assumption 5. Geographical frontiers do not alter

The fundamental diffusion model does not explicitly consider the spatial diffusion[30] of an innovation, as it assumes that an innovation is confined to a geographical area or a certain marketing sector.

Spatial diffusion research focuses on understanding, describing and/or modeling the processes by which spatially defined markets change structure and how individuals adjust their spatial behavior in response to new stimuli (Allaway, Berkowitz and D'Souza, 2003). Earlier models of the innovation diffusion process emphasize the time dependence of diffusion phenomena at the expense of their spatial character (Haynes, Mahajan and White, 1977). However, Casetti and Semple (1969), Haynes, Mahajan and White (1977) and Mahajan and Peterson

[30] The interest in spatial diffusion comes, mainly, from geographers (Brown, 1981).

(1979) extend the diffusion model of mixed influence by integrating space and time dimensions of the diffusion of an innovation.

Geographers like Hägerstrand (1967) introduce an alternative view of the diffusion of innovations by considering it as a question of level of spatial aggregation[31]. Diffusion is considered to be a process of transformation through which a population with few adopters becomes a population with a great number thanks to social interaction and sources of one-directional communication (such as the mass media). Hägerstrand describes the diffusion of an innovation as a three-stage process:

- Stage 1. The first stage develops local concentrations of initial acceptations of an innovation, which the author refers to as "initial agglomerations".
- Stage 2. The second stage reveals the radial dissemination of the innovation. Beginning with the initial agglomerations there is a growth of secondary agglomerations accompanied by a simultaneous condensing of the original centers.
- Stage 3. In the third stage, growth ceases as the process enters a phase of saturation.

Hägerstrand's study identifies three empirical regularities (Mahajan and Peterson, 1979; Mahajan and Wind, 1986). Firstly, an S-shaped diffusion curve (as found by other authors in studies of innovation diffusion); secondly, a hierarchic effect with which we expect diffusion to spread from large to smaller centers (Gore and Lavaraj, 1987) and thirdly, a neighborhood effect (Mahajan and Peterson, 1979), which involves diffusion in a wavelike fashion from an urban centre towards outlying areas and later other, more remote areas.

Although most diffusion models focus on a single market (one geographical region), there are some authors studying multi-market diffusion[32]. These authors are interested in discovering how a single innovation is diffused in different geographical areas or in how the diffusion of an innovation in a certain area affects its diffusion in nearby areas (e.g. neighboring countries). It is interesting and challenging to analyze what would happen if an innovation diffuses in parallel in two neighboring but culturally different geographical areas. Researchers are also looking for similar behavioral patterns in adopters from different geographical areas (near or far). We should bear in mind that, from a business point of view, it is very important for management to understand how a given innovation is diffused in different geographical areas, as this information allows them to compare diffusion

[31] A significant body of spatial diffusion theory exists in geography and sociology as a result of the work of authors like Hägerstrand (1967), Morrill (1970), Brown (1968, 1969, 1981), Morrill, Gaile and Thrall (1988) and Wojan (1998).

[32] See Dekimpe, Parker and Sarvary (2000 a) for a comprehensive review of multi-market diffusion.

rates and to implement more effective marketing strategies when introducing their products into these and other similar areas.

There has been a logical increase in interest in multi-market diffusion given that, as Dekimpe, Parker and Sarvary (2000a, p.50) point out "... *recent economic trends (such as the removal of political and trade barriers and saturated home markets) and the rapid globalization of world markets, more firms are interested in launching products in multiple countries or even on a global basis*". Researchers view multi-market diffusion (a multi-regional or an international context) from two different perspectives. On the one hand, authors select a diffusion model (of external, internal or mixed influence) and use it to analyze the diffusion process of innovations in different markets or geographical areas. On the other hand, authors extend the classical diffusion models by allowing some interactions among different geographical areas or by taking into account the specific characteristics of each geographical area. Some of these authors extend the classical models by introducing a "learning parameter"[33] into the model to capture the learning effect that takes place between the different social systems (i.e. geographical areas), and hence to examine the relationship between lead and lag countries. Within the first perspective, we find authors like Heeler and Hustad (1980), Horsky and Simon (1983), Kobrin (1985), Takada and Jain (1991), Helsen, Jedidi and DeSarbo (1993), Redmond (1994) and Kim, Chang and Shocker (2000). Within the second perspective, we find authors like Eliashberg and Helsen (1996), Gore and Lavaraj (1987), Gatignon, Eliashberg and Robertson (1989), Mahajan and Muller (1994), Jain and Maesincee (1995), Kalish, Mahajan and Muller (1995), Ganesh and Kumar (1996), Ganesh, Kumar and Subramaniam (1997), Putsis, Balasubramanian, Kaplan and Sen (1997), Dekimpe, Parker and Sarvary (1998), Kumar, Ganesh and Echambadi (1998), Dekimpe, Parker and Sarvary (2000b, 2000c), Kumar and Krishnan (2002), Talukdar, Sudhir and Ainslie (2002) and Allaway, Berkowitz and D'Souza (2003).

Although we are not going to cover this work in detail, we will summarize the four empirical generalizations detected by Dekimpe, Parker and Sarvary (2000a) on this topic:

i. The studies show that the wealth of a country has a positive effect on the diffusion process. This means that the greater the wealth of a country, the quicker it tries an innovation and the quicker the diffusion speed within the country.

[33] Ganesh and Kumar (1996, p.332) explain that the learning parameter "*represents the influence of the adopters in the lead country on the potential adopters in the lag countries*".

ii. There are consistent findings of cross-national learning effects, implying that later adopters benefit from the experiences of other countries with an innovation.
iii. Some studies have found that the size of this cross-regional experience is not homogeneous.
iv. It is found that heterogeneity in the social system has a negative effect on diffusion.

2.4.2.6. Assumption 6. The innovation is diffused in isolation

This assumption implies that the diffusion of an innovation is independent of all other innovations; thus, product interactions and competition among firms do not affect the diffusion processes of innovations.

Multi-product interactions

The fundamental diffusion model does not consider relationships between different product categories; thus it holds that the adoption of an innovation does not complement, substitute, eliminate or enhance the adoption of another product (or vice versa). If we accept the fact that an innovation introduced into a market cannot remain isolated, we have to accept the possibility that another innovation or existing product can both positively or negatively influence its diffusion process. The market success of a given innovation may even be aided by another product (multi-product interactions) or product generation (successive generations)[34].

Bayus, Kim and Shocker (2000)[35] point out the relatively little attention that multi-product growth models have received compared to other topics dealing with the diffusion of new products. Table 2.6 shows the existing research on modeling the interactions among multiple products within the diffusion framework of new products.

[34] In fact successive product generations can be regarded as a particular case of multiproduct interactions. As we are not going to focus on technological substitution between successive generations, for a comprehensive review of that extensive literature see Norton and Bass (1987), Kumar and Kumar (1992), Jiménez (1996) and Bayus, Kim and Shocker (2000).

[35] Bayus, Kim and Shocker (2000) develop an expanded conceptual framework for multi-product interactions (Figure 7.3, p.155).

Table 2.6.
Models assuming multi-product interactions.

Reference	Extended model	Innovation context	Purpose	Kind of interaction
Peterson and Mahajan (1978)	Mixed influence	Durable consumer products (black and white TVs and color TVs) Firm services (insurance policies)	Impact of relationships among products	Independent, complementary, contingent and substitute innovations
Bayus (1987)	Mixed influence	Durable consumer products (compact disc player and discs)	Impact of relationships among products	Contingent innovations
Mahajan and Muller (1991)	Mixed influence	Durable and non-durable products (simulation)	Normative purposes (optimal pricing strategies)	Contingent innovations
Bucklin and Sengupta (1993)	Mixed influence	Durable products (supermarket laser scanners and Universal Product Code (UPC) symbols)	Impact of relationships among products	Complementary innovations
Givon, Mahajan and Muller (1995)	Mixed influence	Durable products (spreadsheets and word processors)	Impact of piracy	Legal versus illegal users
Givon, Mahajan and Muller (1997)	Mixed influence	Durable products (spreadsheets and word processors)	Impact of piracy and brand switching	Legal versus illegal users
Kim, Chang and Shocker (2000)	Mixed influence	Durable products (pager, cellular phone (analog and digital) and CT2 (cordless telephone 2))	Incorporation of interproduct category and technological substitution effects simultaneously	Substitute innovations

Peterson and Mahajan (1978) are the first to consider interproduct interactions in the diffusion processes of innovations in marketing literature. They suggest that before analyzing the growth of a product category, it is important to examine its possible relationship with other categories. The authors extend the mixed influence diffusion model by developing four classes of multi-product growth models (independent products, complementary products, contingent products, and substitute products)[36]. They provide two applications to empirically demonstrate two of their models: substitute and independent products. Black-and-white and color televisions are used in the case of substitute products, and two insurance policies adopted by firms in the case of independent products. The results show

[36] "*Independent: sales of one product have no influence upon sales of other products; complementary: increased sales of one product result in increased sales of other products; contingent: sales of one product are conditional upon those of other products; substitute: increased sales of one product produce decreased sales of other products*" (Peterson and Mahajan, 1978, p.208)

that the growth in sales of color television sets had a substitution effect on the sales growth of black-and-white televisions sets, but not the reverse. For the independent case, the results show that there is a substantial improvement when going from a single to a two-product growth model.

Bayus (1987) builds a model to predict the sales of technologies contingent upon the adoption of others. He extends the mixed influence diffusion model by presenting a model that focuses on generating estimates for the primary (i.e. hardware) and the secondary (i.e. software) product at the product category level. To illustrate a practical application of his model, Bayus examines the compact disc player and the acquisition of the associated discs. The results show that his approach provides good forecasts for the compact disc prerecorded audio market.

Mahajan and Muller (1991) study contingent product relationships and develop propositions to specify pricing strategy for primary and contingent products. Some normative results emerge from a simulation study.

Bucklin and Sengupta (1993) explore the co-diffusion[37] of complementary innovations. They extend the mixed influence diffusion model through to the complementary products models developed by Peterson and Mahajan (1978). They empirically study the co-diffusion of laser scanners in supermarkets and the use of the Universal Product Code (UPC) symbols, read by such scanners. The results indicate that a faster rate of adoption of the UPC symbols would have accelerated the diffusion of laser scanners among retailers. They demonstrate the managerial importance of extending marketing strategies to encompass the co-diffusion of related technologies.

Givon, Mahajan and Muller (1995, 1997) extend the Bass model and demonstrate how shadow diffusion of a software may influence its legal diffusion. Their diffusion modeling approach captures the growth of a software over time taking into consideration the influence of pirates on the software diffusion. They analyze the dominant role that pirates play in converting potential users in users of the software. Adoption data from spreadsheets and word processors in the United Kingdom are used to illustrate the application of their model. The results show that the intensity of the word-of-mouth communication of buyers and pirates on potential software users is almost the same. Furthermore, the results indicate that pirates contribute to generating more than 80 percent of the unit sales for these two types of software.

Kim, Chang and Shocker (2000) develop a market growth model for the information technology industry that captures both interproduct dynamics and technological substitution between the successive generations of a single category. They develop a Bass-type diffusion model by extending the Norton and Bass

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[37] By co-diffusion they mean "*the positive interaction between the demands for complementary innovations that have separate adoption tracks. This interaction arises because the adoption of one innovation enhances the value of the other to the end-user.*"(Bucklin and Sengupta, 1993, p. 149)

(1987) model for successive generations. Kim, Chang and Shocker are pioneers in integrating interproduct category dynamics into a market growth model. The results from Hong Kong and Korea data reveal intercategory effects and the importance of using first generation experience as a good analogy in forecasting second generation sales.

Competition

As it is assumed that an innovation is diffused in isolation, the fundamental diffusion model does not consider possible competition[38] between companies or brands. However, sales of a new product are conditioned by both the number of companies and the competition type that arises between them during the diffusion process.

As Mahajan and Wind (1986) (see Table 2.7) point out, the basic diffusion models are, by definition, designed to represent the growth of a product category; i.e. the growth of *n(t)* or *N(t)*.

Table 2.7.
An industry with *K* competitors.

	Time					
Firm or Brand	1	2	…	t	…	T
1	n_{11}	n_{12}	…	n_{1t}	…	n_{1T}
2	n_{21}	n_{22}	…	n_{2t}	…	n_{2T}
.	.	.		.		.
.	.	.		.		.
.	.	.		.		.
k	n_{k1}	n_{k2}	…	n_{kt}	…	n_{1T}
.	.	.		.		.
.	.	.		.		.
.	.	.		.		.
K	n_{K1}	n_{K2}	…	n_{Kt}	…	n_{KT}
Period sales	$N(1)$	$n(2)$	…	$n(t)$	…	$n(T)$
Cumulative sales	$N(1)$	$N(2)$	…	$N(t)$	…	$N(T)$

Source: Mahajan and Wind (1986, p.17)

If we consider an industry with k competitors, $k = 1, 2...,K$, in which each one produces a single durable product brand, and we denote $n(t)$ as the total number of adopters of a product category at time t, $N(t)$ the cumulative number of adopters at time t and n_{it} the number of adopters of brand i at time t, we find that:

[38] See Dolan, Jeuland and Muller (1986) and Chatterjee, Eliashberg and Rao (2000) for a critical review of diffusion models incorporating competition.

$N(T)=\sum_{t=1}^{T} n(t)$ where $n(t)=\sum_{i=1}^{k} n_{it}$. Consequently, unless there is only one company in an industry (a monopoly), the basic diffusion models are not appropriate for modeling brand growth or for examining the impact of marketing strategies on brand growth.

The amount of research on dynamic diffusion models incorporating the effects of competition (see Table 2.8) reflects the recognition of competition as a key factor influencing marketing decisions in a new product environment (Dolan, Jeuland and Muller, 1986; Chatterjee, Eliashberg and Rao, 2000).

Table 2.8.
Models assuming competition.

Reference	Extended model	Innovation context	Purpose	Number of competitors
Dodson and Muller (1978)	Mixed influence	Durable consumer and non-durable consumer products (no empirical analysis)	Impact of marketing variables	Different brands (without specifying how many)
Lilien, Rao and Kalish (1981)	Mixed influence	Non-durable consumer products (prescription drugs)	Impact of marketing variables	Two brands
Teng and Thompson (1983)	Mixed influence	Durable products (numerical solutions)	Normative purposes (optimal advertising strategies)	Oligopoly (*n* players)
Thompson and Teng (1984)	Mixed influence	Durable products (numerical solutions)	Normative purposes (optimal pricing and advertising strategies)	Oligopoly (*n* players)
Rao and Bass (1985)	Mixed influence	semi-conductor components industry (results on eight products and numerical experiments)	Normative purposes (optimal pricing strategies)	Oligopoly (*n* players)
Eliashberg and Jeuland (1986)	External influence	Durable products (numerical solutions)	Normative purposes (optimal pricing strategies)	Oligopoly (duopoly)
Dockner and Jorgensen (1988b)	Mixed influence	Durable products (analytical results)	Normative purposes (optimal pricing strategies)	Oligopoly (*n* players)
Horsky and Mate (1988)	Mixed influence	Durable products (numerical solutions)	Normative purposes (optimal advertising strategies)	Oligopoly (duopoly)
Rao and Yamada (1988)	Mixed influence	Non-durable consumer products (prescription drugs)	Impact of marketing variables	Twenty brands
Dockner and Jorgensen (1992)	Mixed influence	Durable products (analytical results)	Normative purposes (optimal advertising strategies)	Oligopoly (*n* players)
Mahajan, Sharma and Buzzell (1993)	Mixed influence	Durable products (instant cameras)	Impact of new entrants	Three brands

Table 2.8.
Models assuming competition (continued).

Reference	Extended model	Innovation context	Purpose	Number of competitors
Martins and Nascimento (1993)	External influence	Non-durable products (no empirical analysis; phase diagrams)	Normative purposes (optimal pricing strategies)	Different brands
Hahn, Park, Krishnamurthi and Zoltners (1994)	Mixed influence	Non-durable consumer products (prescription drugs)	Impact of marketing variables	Twenty-one brands
Parker and Gatignon (1994)	Mixed influence	Non-durable consumer products (hair styling mousses)	Impact of marketing variables	Nine brands
Kalish, Mahajan and Muller (1995)	Mixed influence	Durable products (numerical solutions)	Normative purposes (optimal entry strategies)	Oligopoly (duopoly)
Givon, Mahajan and Muller (1997)	Mixed influence	Durable products (spreadsheets and word processors)	Impact of piracy and brand switching	Legal versus illegal users
Krishnan, Bass and Kumar (2000)	Mixed influence	Services (cellular telephones subscribers)	Impact of new entrants	Three brands

Table 2.8 shows analytical models providing normative insights and descriptive models for empirical analysis focused on competition among firms. Within the first group of models we find those of Teng and Thompson (1983), Horsky and Mate (1988) and Dockner and Jorgensen (1992), which focus on optimal advertising strategies; the studies of Rao and Bass (1985), Eliashberg and Jeuland (1986), Dockner and Jorgensen (1988b) and Martins and Nascimento (1993), which focus on optimal pricing strategies; the study of Thompson and Teng (1984), which focuses on both optimal advertising and pricing strategies; and that of Kalish, Mahajan and Muller (1995), which focuses on optimal entry strategies. We do not, however, discuss normative purposes, but we deal with the second group of models.

Dodson and Muller (1978) incorporate the possibility of brand switching into their diffusion models. However, these authors do not provide any empirical application.

Lilien, Rao and Kalish (1981) by extending the mixed influence diffusion model, propose a trial-repeat diffusion model where promotional efforts by the firm and competitors are taken into account. Their model is validated on two prescription drugs. The authors, analyzing detailing expenditures, get significant although small estimates for own and competitor detailing effectiveness. (This model is discussed in more detail in Chapter 6).

Rao and Yamada (1988) provide support to the Lilien, Rao and Kalish (1981) model by analyzing twenty prescription drugs. Their results confirm that promotional activities by the firm and competitors affect the diffusion process.

Mahajan, Sharma and Buzzell (1993) extend the mixed influence model to assess the impact of competitive entry on market size and the sales of incumbent firms. In their context a new competitor enters into the market previously served by a single firm that sells an old and a new brand. They provide an empirical application based on data from the United States instant camera market (Polaroid against Kodak). The results reveal that the growth of the two brands of the incumbent firm (Polaroid) is mainly driven by external influence. However, the growth of the new entrant (Kodak) is driven by both the external influence and, possibly, by the internal influence (word-of-mouth communication).

Hahn et al. (1994) extend the mixed influence diffusion model by considering that promotional efforts by the firm and its competitors affect external influence. Their model is validated on twenty-one prescription drugs in seven different product classes. Their results show that, in general terms, promotional efforts (detailing and journal advertising) by the firm and competitors affect the external influence parameter. (This model is discussed in more detail in Chapter 6).

Parker and Gatignon (1994) address the impact of competitive marketing variables (price and advertising) on the diffusion process of brands in competition. They consider nine different brands in the hair styling mousse product category. The results show that each brand is characterized by a different diffusion process specification, revealing that in this context it is not possible to find a unique diffusion model that best characterizes the diffusion process of all the brands in the same category.

Givon, Mahajan and Muller (1997) extend their previous model (Givon, Mahajan and Muller, 1995) to explicitly consider brand switching as well as both legal and illegal use of competitive software brands. As in their previous study, the authors examine the diffusion of major software brands for two software product categories (spreadsheets and word processors) in the United Kingdom. The results show that a firm must develop market share estimates based on users rather than unit sales in the presence of differential piracy and brand switching.

Krishnan, Bass and Kumar (2000) extend the mixed influence diffusion model - in fact the Bass model- to analyze the impact of a later entrant on the sales growth of the category and the existing brands. To test their model, the authors use cellular telephone adoption data in multiple markets. The results reveal good performance for the proposed model.

The studies in this section reveal product interactions and competition among brands or firms as relevant factors that can condition the diffusion process of the majority of innovations. Models assuming multi-product interactions are validated on durables and only the model developed by Peterson and Mahajan (1978) is tested on a different innovation: a service (insurance policies). The researchers address all kinds of interaction: complementary, contingent and substitute interactions. Also, legal versus illegal relationships, a critical interaction that concerns managers, has been studied through diffusion models. The results show that the diffusion process of an innovation can be partly influenced by the diffusion of a related product. Hence, the knowledge of this kind of influence can help managers to develop appropriate marketing strategies to favor the diffusion processes of innovations. However, the multi-product growth models still receive relatively little attention from researchers. The studies that develop models assuming competition have received more attention. One group of researchers (that we do not address in detail) has focused on normative purposes and another on analyzing the impact of marketing variables or a specific event (such as new entrances or piracy). The last group has studied different kinds of innovations: services, durable and non-durable products. Their results show how the diffusion process of an innovation is conditioned by competitors in different ways, such as marketing activity or moment of entry. This may result in different diffusion processes for different brands in the same category and, hence, they are better characterized by different diffusion models.

2.4.2.7. Assumption 7. The characteristics of an innovation or its perception do not change

The assumption that the characteristics of an innovation or its perception do not change in its life time is not adequate for many products, especially for those which are subject to continuous modifications and improvements. An example is the case of new technology such as personal computers[39]. Neither do the basic diffusion models explicitly consider the impact of an innovation's characteristics or its perception among potential adopters; they tend to consider that all innovations are equal. By ignoring the effect of an innovation's perceived attributes on its adoption rate, these models are disregarding the fact that empirical studies such as those of Tornatzky and Klein (1982), Rogers (1983), Winer (1985) or Holak, Lehmann and Sultan (1987) find sufficient evidence to confirm that adopter perception of an innovation's attributes conditions the rate of adoption[40].

[39] Diffusion of successive generations of products should also be included here. As we have stated in assumption 4, given the amplitude of this research area, we are not going to enter into more detail. Of course, it is important to know that this area exists.

[40] Tornatzky and Klein (1982), in a meta-analysis of seventy-five studies, detect that there is stronger empirical support for the relationship of relative advantage, compatibility and complexity with adoption rate, than for those for trialability and observability. Rogers (1983) after an exhaustive

The mathematical formulation of diffusion models, e.g. the Bass model, implicitly assumes that the potential adopter population is homogeneous (Tanny and Derzko, 1988; Chatterjee and Eliashberg, 1990); that is, all individuals who are yet to adopt, have, at any point within the diffusion process, the same probability of adopting in a given time period, and "*differences in individual adoption times are purely stochastic*" (Chatterjee and Eliashberg, 1990, p.1058).

Authors such as De Palma, Droesbeke and Lefevre (1984), Kalish (1985), Srivastava et al. (1985), Kalish and Lilien (1986a, 1986b) and El Ouardighi and Tapiero (1998) relax the seventh assumption, which underlies the fundamental diffusion model.

De Palma, Droesbeke and Lefevre (1984) extend the mixed influence model by considering that the rate of diffusion can depend on the price of the product and its characteristics (such as quality or usefulness); these are measured by a utility function. The authors do not present any empirical application.

Kalish (1985) assumes a heterogeneous population with regard to the valuation of the product. The adoption of a new product is divided into awareness and adoption. To model adoption, Kalish proposes a model that is conditional on awareness and the perceived risk adjusted value of the product. He presents an application of his model on an unspecified durable product. His model provides good fit to the data.

Srivastava et al. (1985) extend the mixed influence diffusion model by considering that external and internal influences are functions of relevant innovation attributes. They develop a multi-attribute diffusion model to forecast the acceptance of potential investment alternatives for consumers. Although they propose a variety of attributes, only the perceived likelihood of negative return and the perceived information cost are considered in their analysis. Their results confirm that the incorporation of information on the innovation attributes improves the capacity of the model to predict diffusion patterns.

Kalish and Lilien (1986a, 1986b) extend the mixed influence model by considering a dynamic potential market and by assuming internal influence as a perceived product-quality feedback term. The authors provide an empirical application based on data on a new photovoltaic system and the results show that the fit is good and the parameters have correct signs, good significance levels and proper magnitudes.

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analysis of a large number of studies, indicates that between 49% and 87% of variation in adoption rates is generally explained by adopter perceptions of the five innovation attributes (relative advantage, compatibility, complexity, trialability and observability). Winer (1985) and Holak, Lehmann and Sultan (1987) investigate the role that consumer expectations play in the adoption of consumer durables.

El Ouardighi and Tapiero (1998) introduce a general diffusion model where the quality of the product is the only control variable. They show that price acts as a signal of quality in the context of diffusion. The analytical results suggest that when the speed of diffusion is insufficient to fill unit profit margin erosion induced by product cycle aging, quality must increase to stimulate it more.

In addition to the aggregate-level diffusion perspective, Roberts and Urban (1988) are pioneers in the transfer of the individual behavioral framework from economics to marketing[41]. Authors, such as Chatterjee and Eliashberg (1990), develop models that consider potential adopter perception of the relevant innovation attributes from a disaggregate-level model approach. Although we do not focus on the disaggregate-level diffusion models, it is interesting to know that Chatterjee and Eliashberg (1990) develop a flexible diffusion model that incorporates heterogeneity in the population along with other dimensions -such as initial perceptions of the performance of the innovation, key determinants of preference (risk attitude and price sensitivity) and responsiveness to information on the innovation- that affect the individual adoption decision. They present an aggregate diffusion model that, based on individual-level behavior, describes the diffusion process of an innovation (a high involvement durable or service) in a heterogeneous population.

2.4.2.8. Assumption 8. There are no supply restrictions

Looking at the nature of the fundamental diffusion models, we see that they are demand models.

The inability to capture supply restrictions is another shortcoming attributed to diffusion models[42]. The scarcity of a new product in the market (for example, due to constraints in productive capacity or deficiencies in the distribution process) could increase the number of potential adopters (Simon and Sebastian, 1987). If the demand for a new product exceeds its supply, the distribution of adopters corresponds with the supply distribution and not with the distribution of the demand for the product (Mahajan, Muller and Bass, 1993).

Jain, Mahajan and Muller (1991) are the first authors who address this shortcoming of diffusion models by explicitly modeling supply-side constraints.

[41] See Hiebert (1974), Stoneman (1981), Feder and O'Mara (1982) and Jensen (1982) for pioneering models of adoption of innovations using micro-modeling approaches (disaggregate-level perspective) in economics literature.

[42] Urban, Hauser and Roberts (1990) consider the influence of supply restrictions on consumer preferences and on the demand for new products.

They point out that supply restrictions can lead to a queue of potential consumers. They distinguish three kinds of adopters: potential adopters, waiting applicants and current adopters. The application of their model is illustrated using data from new telephones in Israel.

Other authors modeling the diffusion process of innovations in an environment with supply restrictions are Ho, Savin and Terwiesch (2002), Kumar and Swaminathan (2003) and Swami and Khairnar (2003). Ho, Savin and Terwiesch (2002) model a constrained new product diffusion situation from a supply chain management perspective, and they present a numerical study. Kumar and Swaminathan (2003) consider a more general setting than that considered by Ho, Savin and Terwiesch (2002). Their model is capable of handling a variety of scenarios for backlogging unmet demand, ranging from complete backlogging to lost sales. Like the previous authors, they present a numerical study. Swami and Khairnar (2003) model a situation in which a limited quantity product ceases to remain available after a certain point in time. They apply their model to the case of a performing arts company selling seats before a concert.

2.4.2.9. Assumption 9. The impact of marketing strategies is implicitly captured by the model parameters

The classical diffusion models are parsimonious models that quantify the diffusion phenomenon and capture its essence with the help of only a few parameters. Although these parameters have clear theoretical interpretation and implicitly capture the impact of marketing variables on the diffusion process of an innovation, the classical diffusion models do not provide an understanding of the specific effect of these variables. This has led certain economists, such as Russell (1980), to describe innovation diffusion models as incomplete. The explicit incorporation of marketing variables not only gives the model greater realism but also contributes to better business management by considering the possibility of altering the diffusion process through marketing control. In fact, the importance of marketing mix variables in diffusion models has been pointed out by diffusion scholars (Mahajan and Muller, 1979; Kalish and Sen, 1986; Mahajan and Wind, 1986, 1988; Mahajan, Muller and Bass, 1990; Bass, Jain and Krishnan, 2000). As these authors point out, the incorporation of marketing mix variables into diffusion models is important because, in this way, the effect of marketing on diffusion can be measured and marketing strategies for new products can be improved. Jorgensen (1983, p. 269) points out "*In a marketing context, the purpose of the model is to describe and predict the increase over time in the number of adopters of a new product. However, from a product manager's point of view, many diffusion models may not be very useful since they fail to incorporate the firm's marketing decision variables such as price and advertising*".

The importance of explicitly considering marketing variables in diffusion models obliges us to dedicate special attention to this topic. Some relevant questions arise:

- Which parameters are influenced by marketing mix variables?
- Which functional form is appropriate for incorporating marketing mix variables into diffusion models?

Although a lot of studies concerning marketing variables in the diffusion process have been developed, there are no conclusive answers to these questions. Theoretically, marketing variables can affect external influence[43], internal influence[44] and/or potential market. Table 2.9 shows how to include marketing variables in diffusion models. More options can be obtained by combining those shown in the table. Nevertheless, although some combinations can be theoretically appealing, we have to remember that econometrical problems can rise when parameters are estimated (Simon and Sebastian, 1987). Examples of these problems are multicollinearity problems.

Table 2.9.
Marketing variables in diffusion models

Marketing variables affect[(*)] ...

… external influence (with a non-separable function of the diffusion process)

$$n(t)=\frac{dN(t)}{d(t)}=\left(\beta_1(t)+\beta_2\frac{N(t)}{M}\right)\left[M-N(t)\right]$$

where $\beta_1(t)=f(\text{marketing variables}(t))$

… internal influence (with a non-separable function of the diffusion process)

$$n(t)=\frac{dN(t)}{d(t)}=\left(\beta_1+\beta_2(t)\frac{N(t)}{M}\right)\left[M-N(t)\right]$$

where $\beta_2(t)=f(\text{marketing variables}(t))$

… both external and internal influence (with a non-separable function of the diffusion process)

$$n(t)=\frac{dN(t)}{d(t)}=\left(\beta_1(t)+\beta_2(t)\frac{N(t)}{M}\right)\left[M-N(t)\right]$$

where $\beta_1(t)=f_1(\text{marketing variables}(t))$ and $\beta_2(t)=f_2(\text{marketing variables}(t))$

… both external and internal influence (with a separable function of the diffusion process)

$$n(t)=\frac{dN(t)}{d(t)}=\left(\beta_1+\beta_2\frac{N(t)}{M}\right)f(\text{marketing variables}(t))\left[M-N(t)\right]$$

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[43] In this case, marketing variables affect the adoption decision of a potential adopter without being influenced by information from an early adopter.

[44] In this case, marketing variables stimulate interpersonal communication.

Table 2.9.
Marketing variables in diffusion models (continued)

… potential market (with a non-separable function of the diffusion process)

$$n(t) = \frac{dN(t)}{d(t)} = \left(\beta_1 + \beta_2 \frac{N(t)}{M(t)}\right)\left[M(t) - N(t)\right]$$

where $M(t) = f(\text{marketing variables}(t))$

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where
$n(t)=dN(t)/dt$: non-cumulative number of adopters at time t or the rate of diffusion at time t
$N(t)$: cumulative number of adopters at time t
M: potential market
β_1: parameter of external influence
β_2: parameter of internal influence
marketing variables(t): marketing variables at time t
$f(.)$: functional shape of the influence of marketing variables
$\beta_1(t)$: time-varying parameter of external influence
$\beta_2(t)$: time-varying parameter of internal influence
$M(t)$: dynamic potential market

(*): Internal influence is represented by $bN(t)$ instead of $\beta_2(N(t)/M)$ if the Mahajan and Peterson (1985) specification is used.

Many authors have worked on relaxing this assumption (i.e. implicit consideration of marketing variables) to improve the realism of diffusion models. We briefly discuss some of the studies that explicitly incorporate marketing variables into diffusion models. Although some of these studies have already been mentioned in the context of other assumptions, we refer to them again here because their models are also examples of models which explicitly consider marketing efforts. In this case, we only point out parts of the models related to marketing variables (i.e. assumption 9). Table 2.10 shows these studies according to four dimensions: the kind of influence (external, internal or mixed) considered in the diffusion model, the type of innovation analyzed, the study's purpose and the marketing variables incorporated.

The model developed by Chatterjee and Eliashberg (1990) is not included because they develop an individual-level diffusion model. We also do not consider models within the proportional-hazard framework (Cox, 1972) introduced into marketing by Jain and Vilcassim (1991), Jain (1992) and Helsen and Schmittlein (1993); these models also incorporate differences in terms of the underlying consumer characteristics. This research is beyond the scope of our study.

Table 2.10.
Models considering marketing mix variables.

Reference	Extended model	Innovation context	Purpose	Marketing mix variables
Robinson and Lakhani (1975)	Mixed influence	Consumer durable technological products (semiconductor device; an illustrative example)	Normative purposes (optimal pricing strategy) monopoly	Price
Dodson and Muller (1978)	Mixed influence	Durable consumer and non-durable consumer products (no empirical analysis)	Impact of marketing variables competition	Advertising
Bass (1980)	Mixed influence	Consumer durable technological products (electric refrigerators, room air conditioners, automatic dishwashers, black and white TVs, electric clothes dryers, color TVs	Normative purposes (optimal pricing strategy) monopoly	Price
Dolan and Jeuland (1981)	Mixed influence	Durable consumer and non-durable consumer products (simulation, no analytical results)	Normative purposes (optimal pricing strategy) monopoly	Price
Lilien, Rao and Kalish (1981)	Mixed influence	Non-durable consumer products (prescription drugs)	Impact of marketing variables competition	Detailing
Bass and Bultez (1982)	Mixed influence	Durable products (simulation, no analytical results)	Normative purposes (optimal pricing strategy) monopoly	Price
Feichtinger (1982)	Mixed influence	New product (unspecified) (phase diagram)	Normative purposes (optimal pricing strategy) monopoly	Price
Jeuland and Dolan (1982)	Mixed influence	Non-durable products (simulation, no analytical results)	Normative purposes (optimal pricing strategy) monopoly	Price
Horsky and Simon (1983)	Mixed influence	Durable products (telephonic banking as a new system)	Normative purposes (optimal advertising strategy) monopoly	Advertising
Jorgensen (1983)	Mixed influence	Durable products (no empirical application)	Normative purposes (optimal pricing strategy) monopoly	Price
Kalish (1983)	Mixed influence	Durable and non-durable products (no empirical application)	Normative purposes (optimal pricing strategies) monopoly	Price

Table 2.10.
Models considering marketing mix variables (continued).

Reference	Extended model	Innovation context	Purpose	Marketing mix variables
Teng and Thompson (1983)	Mixed influence	Durable products (numerical solutions)	Normative purposes (optimal advertising strategies) competition	Advertising
De Palma, Droesbeke, Lefevre and Rosinski (1984)	Mixed influence	Durable products (no empirical application)	Impact of marketing variables no competition	Price
Thompson and Teng (1984)	Mixed influence	Durable products (numerical solutions)	Normative purposes (optimal pricing and advertising strategies) competition	Price Advertising
Kalish (1985)	Mixed influence	Durable consumer and non-durable consumer products (unspecified)	Normative purposes (optimal pricing and advertising strategies) monopoly	Price Advertising
Rao and Bass (1985)	Mixed influence	semi-conductor components industry (results on eight products and numerical experiments)	Normative purposes (optimal pricing strategies) competition	Price
Eliashberg and Jeuland (1986)	External influence	Durable products (numerical simulations)	Normative purposes (optimal pricing strategies) competition	Price
Kalish and Lilien (1986a, 1986b)	Mixed influence	Durable consumer product (photovoltaic system)	Impact of marketing variables no competition	Price
Kamakura and Balasubramanian (1987)	Mixed influence	Consumer durable technological products (refrigerators, vacuum cleaners, toasters, electric blankets)	Impact of marketing variables no competition	Price
Simon and Sebastian (1987)	Mixed influence	Durable technological products (telephones)	Impact of marketing variables no competition	Advertising
Dockner and Jorgensen (1988a)	Mixed influence	Durable products (no empirical application)	Normative purposes (optimal advertising strategies) monopoly	Advertising

Table 2.10.
Models considering marketing mix variables (continued).

Reference	Extended model	Innovation context	Purpose	Marketing mix variables
Dockner and Jorgensen (1988b)	Mixed influence	Durable products (analytical results)	Normative purposes (optimal pricing strategies) competition	Price
Horsky and Mate (1988)	Mixed influence	Durable products (numerical solutions)	Normative purposes (optimal advertising strategies) competition	Advertising
Kamakura and Balasubramanian (1988)	External, Internal and Mixed influence	Consumer durable technological products (air conditioners, refrigerators, vacuum cleaners, toasters, blenders, mixers)	Impact of marketing variables no competition	Price
Rao and Yamada (1988)	Mixed influence	Non-durable consumer products (prescription drugs)	Impact of marketing variables competition	Detailing
Horsky (1990)	Mixed influence	Consumer durable technological products (black and white TVs, color TVs, dishwashers, clothes dryers)	Normative purposes (optimal pricing strategy) monopoly	Price
Jain and Rao (1990)	Mixed influence	Consumer durable technological products (room air conditioners, clothes dryers, color TVs, can openers)	Impact of marketing variables no competition	Price
Bhargava, Bhargava and Jain (1991)	Mixed influence	Durable consumer products (color TVs)	Impact of marketing variables no competition	Price
Jones and Ritz (1991)	Mixed influence (equation system)	Durable consumer products (movies)	Impact of marketing variables no competition	Distribution
Mahajan and Muller (1991)	Mixed influence	Durable products (simulation)	Normative purposes (optimal pricing strategy) monopoly	Price
Dockner and Jorgensen (1992)	Mixed influence	Durable products (analytical results)	Normative purposes (optimal advertising strategies) competition	Advertising

Table 2.10.
Models considering marketing mix variables (continued).

Reference	Extended model	Innovation context	Purpose	Marketing mix variables
Parker (1992)	Mixed influence	Consumer durable technological products (bed covers, blenders, calculators, clothes dryers, dishwashers, disposers, freezers, ironers, microwave ovens, ranges, built-in rangers, refrigerators, room air conditioners, steam irons, color TVs, black and white TVs, and water pulsators)	Impact of marketing variables no competition	Price
Martins and Nascimento (1993)	External influence	Non-durable products (no empirical application)	Normative purposes (optimal pricing strategy) competition	Price
Bass, Krishnan and Jain (1994)	Mixed influence	Consumer durable technological products (room air conditioners, clothes dryers, color TVs)	Impact of marketing variables no competition	Price Advertising
Hahn, Park, Krishnamurthi and Zoltners (1994)	Mixed influence	Consumer non-durable products (prescription drugs)	Impact of marketing variables competition	Detailing together with medical journal advertising
Parker and Gatignon (1994)	Mixed influence	Non-durable consumer products (hair styling mousses)	Impact of marketing variables competition	Price Advertising
Jain, Mahajan and Muller (1995)	Mixed influence	Durable and non-durable products (numerical solutions)	Normative purposes monopoly	Sampling
Mesak and Berg (1995)	External, Internal and Mixed influence	Consumer durable technological products (dishwashers, electric dryers, disposers, color TVs, refrigerators, freezers, ranges, black and white TVs, air conditioners)	Normative purposes (monopoly) and impact of marketing variables (no competition)	Price
Mesak (1996)	Mixed influence	Consumer durable technological products (cable TV)	Normative purposes (monopoly) and impact of marketing variables (no competition)	Price Advertising Distribution

Table 2.10.
Models considering marketing mix variables (continued).

Reference	Extended model	Innovation context	Purpose	Marketing mix variables
Bottomley and Fildes (1998)	External, Internal and Mixed influence	Consumer durable technological products (color TVs, videocassette recorders, microwave ovens, video-cameras (inc. camcorders), compact disc players -in UK-) (air conditioners, refrigerators, vacuum cleaners, blenders, mixers and toasters -in the USA-)	Impact of marketing variables no competition	Price
Putsis (1998)	Mixed influence	Consumer durable technological products (color TVs, video cassette recorders)	Impact of marketing variables no competition	Price
Krishnan, Bass and Jain (1999)	Mixed influence	Durable products (numerical solutions)	Normative purposes (optimal pricing strategy) monopoly	Price

Robinson and Lakhani (1975) were pioneers in incorporating decision variables into diffusion models. Robinson and Lakhani (1975), Dolan and Jeuland (1981), Bass and Bultez (1982) and Jeuland and Dolan (1982) investigating the optimal strategic pricing of technological innovations, extend the mixed influence model by incorporating price (as a separable function of the diffusion process). Robinson and Lakhani (1975) and Dolan and Jeuland (1981) introduce price into the model using the function:

$$f(P(t)) = e^{-\delta_1 P(t)} \tag{2.76}$$

where $P(t)$ is price at time t and δ_1 is a constant. Bass and Bultez (1982) and Jeuland and Dolan (1982) introduce price into the model using the function:

$$f(P(t)) = P(t)^{-\delta_1} \tag{2.77}$$

where $P(t)$ is price at time t and δ_1 is the price elasticity parameter. All the previous authors use simulations to validate their models.

Dodson and Muller (1978) develop two models that extend the mixed influence diffusion model. The first model is a dynamic mixed influence diffusion model with advertising and social interaction (word-of-mouth); the second model extends the first by incorporating repeat purchases and brand switching. The movement from unawareness of the existence of the product to awareness is considered to be a function of the firm's advertising expenditure. However, these authors do not provide details regarding the estimation procedure, data sources, estimation or specification of initial awareness and the advertising response function.

Bass (1980) proposes a demand model, based on the Bass (1969) model, for consumer durable technological innovations that incorporates price as a separable function of the diffusion process. Bass (1980) uses Equation (2.77) to introduce price into the model. He estimates the model using data on six consumer durable innovations.

Lilien, Rao and Kalish (1981) propose a trial-repeat diffusion model with promotional efforts (specifically detailing) that represents an extension to the mixed influence model. They test their model using data on two prescription drugs and get significant although small estimates for detailing effectiveness. The results show that detailing affects the diffusion process of the analyzed prescription drugs. (This model is discussed in more detail in Chapter 6).

Feichtinger (1982) focuses on optimal pricing. He extends the mixed influence model by assuming that price affects the diffusion process of the innovation through the potential market. Feichtinger uses a phase portrait analysis to show the applicability of his model.

Horsky and Simon (1983) extend the mixed influence diffusion model by considering that advertising affects external influence but not internal influence. They provide an empirical application based on data from telephone banking. The results show that advertising affects the diffusion process in the five cities where the new system was introduced.

Jorgensen (1983) focuses on optimal pricing policy. He extends the mixed influence diffusion model by assuming that potential market is a linear-decreasing function of price. Neither empirical nor numerical results are provided.

Kalish (1983) deals with pricing of a new product (durable and non-durable goods) over time. Considering the mixed influence diffusion model, Kalish incorporates price in his model in the same way as Dolan and Jeuland (1981). There is no empirical application.

Teng and Thompson (1983) study competitive encounters among firms and are especially interested in policy questions involving introductions of new products. The control variable available for each firm is advertising. Their monopolistic demand model, which is extended to an oligopoly model, is based on the mixed influence diffusion model. The authors extend the mixed influence diffusion model by allowing the parameters of external and internal influence to be linear functions of advertising (see assumption 3, Equation (2.48)). As with other authors, in the study by Teng and Thompson, analytical complexity makes numerical experiments a useful way to show how their model works.

De Palma, Droesbeke and Lefevre (1984) extend the mixed influence model by considering that price can affect the rate of diffusion (following Robinson and Lakhani (1975) -Equation (2.76)-) and/or the potential market (see assumption 2, Equations (2.32) and (2.33)). The authors do not present any empirical application.

Thompson and Teng (1984) extend their advertising model (Teng and Thompson, 1983) to incorporate the impact of price in the demand specification, via a multiplicative term (following Robinson and Lakhani, 1975) that is a decreasing function of price. The authors show numerical solutions of a number of examples.

Kalish (1985) proposes a model divided into two stages. Advertising is included in the first stage (awareness) and price in the second (adoption). This first stage also depends on cumulative sales of the product, initial potential market and the information that potential adopters have on the new product. The second stage also depends on cumulative sales of the product, initial potential market and the information that potential adopters have on the new product. Although Kalish considers both durable and non-durable goods, he tests his model on an unspecified durable product and the results show that his model provides good fit to the data.

Rao and Bass (1985) propose a pricing model with both dynamic and competitive effects. The authors consider several cases where price can affect the potential market or the adoption rate as a separable function. They use the price function -Equation (2.77)- used by Bass and Bultez (1982) and Jeuland and Dolan (1982). The authors examine price dynamics in the semi-conductor components industry for eight products.

Eliashberg and Jeuland (1986), interested in dynamic pricing strategies for new durable goods in a competitive context, extend the external influence model by incorporating price into the model. They propose two functions for external influence (see assumption 3, Equations (2.51) and (2.52), respectively). The authors provide several numerical simulations.

Kalish and Lilien (1986a, 1986b) introduce price into the mixed influence model by affecting the potential market. The results from data on a new durable product (photovoltaic system) confirm the influence of price on the potential market.

Kamakura and Balasubramanian (1987) extend the mixed influence model by allowing replacement and explicitly incorporating price into the model affecting the potential market. They test their model on four consumer durables. The results show that although the estimates of price show the expected negative sign, they are generally insignificant.

Simon and Sebastian (1987) propose several ways of incorporating advertising into the diffusion model, affecting external or internal influence. Their results show that, although advertising efforts affect both external and internal influence, the model which considers that advertising affects only internal influence is slightly superior.

Dockner and Jorgensen (1988a) investigating optimal advertising strategies for new products in a monopolistic market, propose a mixed influence diffusion model in which external and/or internal influence are dependent on advertising. They incorporate a linear function of advertising into the diffusion model (as non-separable functions) and assume decreasing returns from advertising. Although they propose their model with the introduction of consumer durables in mind, they do not show any empirical application or numerical results.

Dockner and Jorgensen (1988b) extend the mixed influence diffusion model by dealing with optimal pricing policies in a competition context. Specifically, they develop an oligopolistic extension to the Kalish (1983) monopoly pricing model. Following Robinson and Lakhani (1975), they assume that the interaction between adoption rate and price is multiplicative. A linear price specification is considered. The authors derive analytical results for special cases of a general model that includes diffusion and pricing effects. The authors point out that in all cases it seems to be the rule that optimal oligopolistic prices should increase (decrease) whenever there are positive (negative) adoption effects, i.e. past sales stimulate (discourage) current sales.

Horsky and Mate (1988), investigating optimal advertising policies, extend the mixed influence diffusion model by incorporating advertising effects for two firms introducing new durable products. They specify the effectiveness of advertising to be a logarithmic function of advertising expenditure. The authors provide numerical evaluations.

Kamakura and Balasubramanian (1988) extend the diffusion models of external, internal and mixed influence by considering a dynamic potential market and by explicitly incorporating price. They present a nested family of models in which they consider different ways of incorporating price:

- Price only affects the potential market

$$n(t) = g(t)\left[\delta_1 HH(t)P(t)^{\delta_2} - N(t)\right] \tag{2.78}$$

- Price only affects adoption probability

$$n(t) = g(t)P(t)^{\delta_3}\left[\delta_1 HH(t) - N(t)\right] \tag{2.79}$$

- Price affects both adoption probability and the potential market

$$n(t) = g(t)P(t)^{\delta_3}\left[\delta_1 HH(t)P(t)^{\delta_2} - N(t)\right] \tag{2.80}$$

where $HH(t)$ is the number of electrified households at time t, $P(t)$ an index price at time t (deflated by the Consumer Price Index), δ_1 the final penetration level, δ_2 the impact of price on the potential market and δ_3 the impact of price on the probability of adoption. The form of $g(t)$ will depend on the kind of influence considered, it will be $g(t) = a$ for external influence, $g(t) = bN(t)$ for internal influence and $g(t) = a + bN(t)$ for mixed influence. The authors test their specifications on six durable consumer products. Their results show that price does not impact on the lower-priced durables, while it impacts on adoption probability for the relatively higher-priced durables. Hence, when price does impact on the diffusion process, it is achieved through an effect on adoption probability, not through the potential market. Another interesting result is that the mixed influence diffusion model is not always the most parsimonious representation of the diffusion process. It depends on the product category.

Rao and Yamada (1988) provide support for the Lilien, Rao Rao and Kalish (1981) model by analyzing twenty prescription drugs. Their results show that promotional activities affect the diffusion process, given that detailing estimates generally present the expected signs and are significant.

Horsky (1990) develops a model describing a durable purchase decision made by a utility maximizing household. His model extends the mixed influence diffusion model by considering a dynamic potential market. Price, income and the number of households are the variables used to introduce dynamism into the potential market. Data from black and white televisions, color televisions, dishwashers and clothes dryers are used for the empirical application. However, Horsky assumes that a certain percentage of the demand in later years was made up of replacement purchases. As there is no empirical support for this assumption, his results can be questioned (Bass, Jain and Krishnan, 2000).

Jain and Rao (1990), in line with Kamakura and Balasubramanian (1988), extend the mixed influence diffusion model by incorporating price. They use the following functions for price:

$$f_1(P(t)) = P(t)^{\delta_1} \tag{2.81}$$

$$f_2(P(t)) = \frac{1}{\left(1 + \delta_2 P(t)^{-\delta_3}\right)} \tag{2.82}$$

where $P(t)$ is price at time t, and δ_1, δ_2 and δ_3 are constants. The difference between these two studies is that Kamakura and Balasubramanian (1988) use a discrete-time formulation for estimating a continuous model, and Jain and Rao (1990) use the continuous-time formulation. Although using discrete time formulations introduces the possibility of time interval bias, previous research has suggested that parameters do not differ widely according to the estimation method used (Mahajan, Mason and Srinivasan, 1986). Jain and Rao test their models with four durable consumer products: room air conditioners, clothes dryers, color televisions and can openers. Their results show that price has no significant effect on can openers but does affect the adoption rates of the other products. (We address this model again in Chapter 5).

Bhargava, Bhargava and Jain (1991) extend the Bass model by incorporating price. They present four models incorporating price: two models where price affects the potential market (see assumption 2, Equations (2.41) and (2.42)) and two models where price affects the rate of diffusion (using separable functions). The authors use the following functions for price:

- $$f(P(t)) = \left(\frac{P(t)}{P(0)}\right)^{\delta_1} \tag{2.83}$$

- $$f(P(t)) = \exp\left[\delta_2\left(1-\frac{P(t)}{P(0)}\right)\right] \tag{2.84}$$

where $P(t)$ is the inflation-adjusted price at time t, $P(0)$ the initial price at time t=0 and δ_1 and δ_2 are parameters. The authors analyze the diffusion of color televisions in India. They do not find conclusive results regarding price.

Jones and Ritz (1991) propose an equation system in which two different diffusion processes interact: the retailers' diffusion process (producers to retailers), which is represented by a modified Bass model, and the consumers' diffusion process (retailers to consumers), which is represented by a diffusion model of external influence. The data used in this study comes from the movie industry; movies are considered durable products. Although these authors conclude that their model achieves a lower degree of fit than other models –Bass model and NUI model (Easingwood, Mahajan and Muller, 1983)- which only reflect a single consumer process (producer to consumers), its fit is still exceptional and has the benefit of incorporating the effect of distribution.

Mahajan and Muller (1991), focused on pricing strategies for primary and contingent products, assume that price produces a multiplicative effect on the rate of diffusion (separable functions are considered). They analyze two types of contingent relationships. In type one they assume that the primary product can be used without adopting the contingent product and price is introduced into the model following Robinson and Lakhani (1975). In type two, they assumed that the primary product cannot be used without the contingent product and, therefore, the price of the contingent product is important for the decision to adopt the primary product. Thus, for the primary product, the response function for price at time t is given by:

$$f(P(t)) = e^{-\delta_1 P_1(t)-\delta_{12}P_2(t)} \tag{2.85}$$

where P_i (i = 1 or 2) is the price of each product at time t, δ_1 the parameter that measures the price sensitivity of product 1 and δ_{12} the parameter that measures the price cross sensitivity. The term $e^{-\delta_{12}P_2(t)}$ reflects the contingent nature of the products. This term measures the effect on the diffusion of the primary product due to changes in the price of the contingent product. Some normative results emerge from a simulation study.

Dockner and Jorgensen (1992) extend their previous work (Dockner and Jorgensen, 1988a) to oligopolistic competition. They assume that advertising and price are the major sources of influence on sales rate, but due to the complexity involved in considering the two together, they agree to concentrate on advertising effects and to consider exogenously determined price paths. The authors derive analytical results for special cases of a general model that includes advertising effects. In one of the special cases, they consider a generalization of the Horsky and Simon (1983) dynamics to include advertising. Some analytical results are derived.

Parker (1992) focuses on price elasticity dynamics. He extends the mixed influence diffusion model by incorporating price as both a separable and a non-separable function of the diffusion process (we discussed these functions in assumption 3). He analyzes sixteen durable product categories. The results show that for some low and high priced categories, price does not play a major role in the diffusion process. For some low priced categories price impacts on the diffusion process. This is in contrast to Kamakura and Balasubramanian (1988), who find that only for high priced categories does price impact on the diffusion process.

Martins and Nascimento (1993) focus on the diffusion of non-durables in a competitive environment. However, competitive action/reaction is not modeled explicitly even though the dynamics of the model allow for switching in and out of the product and, hence, competitive dynamics are inherently recognized. They extend the external influence diffusion model by allowing adopters not to buy in the following period and by considering dynamic potential market. Price is introduced into their model by affecting the potential market (see assumption 2). Although Martins and Nascimento do not present an empirical application, they derive optimal trajectories using phase diagrams.

Bass, Krishnan and Jain (1994) propose the Generalized Bass Model (GBM)[45]. Their model extends the Bass model by incorporating marketing variables. They assume that price and advertising affect adoption rate and use a separable function of the diffusion process to incorporate these variables into the diffusion model:

$$f(P(t),A(t)) = \left[1 + f_1(P(t)) + f_2(A(t))\right] \tag{2.86}$$

where

$$f_1(P(t)) = \delta_1 \frac{\Delta P(t)}{P(t-1)} \quad \text{and} \tag{2.87}$$

$$f_2(A(t)) = \delta_2 \frac{\Delta A(t)}{A(t-1)} \tag{2.88}$$

where $P(t)$ is price at time t, $\Delta P(t)$ the change in price at time t, $A(t)$ advertising at time t, $\Delta A(t)$ the change in advertising at time t, and δ_1 and δ_2 are parameters. δ_1 and δ_2 are the diffusion price and advertising parameters, respectively, since they control the effect of price and advertising on the diffusion process. They test the model with room air conditioners, clothes dryers and color televisions. The results show that price and advertising have significant effects for room air conditioners and clothes dryers, and price has a significant effect for color televisions. (We address this model again in Chapter 4).

[45] Also see Bass, Jain and Krishnan (2000) for a detailed review of the Generalized Bass model.

Hahn et al. (1994) consider that promotional efforts (detailing and medical journal advertising) affect external influence. Their model is validated on twenty-one prescription drugs in seven different product classes. Their results show that, in general terms, promotional efforts affect external influence. (This model is discussed in more detail in Chapter 6).

Parker and Gatignon (1994) propose alternative specifications of brand–level first purchase diffusion models. They suggest a typology of brand-diffusion processes depending on the nature of interpersonal influences and brand-level competition. They consider nine different brands in the hair styling mousse product category. Although they analyze frequently purchased products, they do not consider repeat purchases in their models. The results show that each brand is characterized by a different diffusion process specification. Although marketing mix variables are critical to the diffusion of brands, their impact is not identical across brands. The results show that the sensitivity of trials to price remains constant or increases over time, but advertising sensitivity can be insignificant, increase or decrease over time, depending on the order of entry.

Jain, Mahajan and Muller (1995) extend the Bass model in order to determine the optimal number of samples that must be available in the marketplace before introducing a new product. Jain, Mahajan and Muller (1995, p. 127) point out that the "*objective of the product sample is to initiate the diffusion process and to influence the adoption curve*". They are pioneers in the study of the effect of this marketing variable on the diffusion of a new product. The authors incorporate sampling effects on the parameter of innovation (see assumption 3, Equation (2.58)). The authors present a numerical analysis for durable and nondurable products. They observe that whereas a high sampling level is appropriate for a product with a high parameter of imitation, it is not for a product with a high parameter of innovation.

Mesak and Berg (1995) extend the diffusion models of external, internal and mixed influence by including price and replacement purchases. Price can affect first purchases and/or repeat purchases. When price affects first purchases, it can be as a separable function affecting adoption rate or as a non-separable function affecting external influence, internal influence or the potential market. Their results on nine durable consumer products show that: i) not all high-priced consumer durables are price sensitive; ii) although first purchases can be price sensitive, replacement purchases may be price sensitive or insensitive, but not vice versa; iii) for the first purchase model and for high-priced consumer durables, price is likely to affect potential market, iv) pricing response functions are similar when first and repeat purchases are price sensitive; v) high-priced consumer durables basically show an imitative diffusion process.

Mesak (1996) starts his work by proposing a general diffusion model that incorporates marketing variables (price, advertising and distribution) and later discusses some specific cases. Mesak extends the mixed influence diffusion model by proposing alternative marketing variables that can affect external influence, internal influence and the potential market. They incorporate the marketing variables through separable and/or non-separable functions. They propose the following functions for price, advertising and distribution:

i) $f_1(P(t)) = P(t)^{-\delta}$ (2.89)

where $P(t)$ is the real (deflated) price index for the average monthly basic rate and δ>1 is a constant,

ii) $f_2(A(t)) = \sqrt{A(t)}$ (2.90)

where $A(t)$ is the real (deflated) index of advertising expenditure, and

iii) $f_3(D(t)) = D(t)$ (2.91)

where $D(t)$ is the distribution index. Mesak finds that price affects external influence, advertising affects diffusion rate, and distribution affects the potential market.

Bottomley and Fildes (1998) examine the role of price in diffusion models through the family of nested diffusion models proposed by Kamakura and Balasubramanian (1988). They consider three sets of diffusion models with a dynamic potential market: a set of external influence, a set of internal influence, and a set of mixed influence. They provide an empirical study on twelve consumer durable categories, six from the United Kingdom and six from the United States of America. They compare models using their fit and their forecasting performance. The results show that, for eight categories out of twelve, the diffusion models that do not incorporate price better explain the diffusion processes. Also, the mixed influence diffusion model is only rarely required to represent the underlying diffusion process. Moreover, there is no single specification to incorporate price into the diffusion models. In the minority of cases, where price affects diffusion process, it impacts on adoption rate rather than on the size of the potential market; although only for high priced durables, a result supported by Kamakura and Balasubramanian (1988) and Jain and Rao (1990). When authors analyze the predictive validity of the models, comparing two models incorporating price (one affecting adoption rate and another affecting the potential market) together with some well-known diffusion models with no price variable, such as the Bass model, the NSRL model (Easingwood, Mahajan and Muller, 1981) and the NUI model (Easingwood, Mahajan and Muller, 1983), the results show that the well-known diffusion models supply more accurate forecasts than the others. Among these other models, it is found that the model in which price affects the adoption rate is more accurate than that in which price affects the potential market. In general, results find no evidence that the best-fitting model produces the most accurate forecast. Bottomley and Fildes (1998, p. 552) conclude by pointing out that "*While including prices may not improve the model's forecasting performance, such* *models may provide a useful decision-support tool with which to analyze alternative pricing scenarios*".

Putsis (1998) extends the mixed influence model. He proposes a flexible diffusion model with varying parameters, price and replacement sales. Putsis validates his model by using data on two consumer durables and the results confirm that the price parameter varies over time.

Krishnan, Bass and Jain (1999) propose a variation of the Generalized Bass model developed by Bass, Krishnan and Jain (1994). Specifically, they assume that the current marketing effort is given by

$$f(P(t)) = \left[\delta_1 + \delta_2 \frac{\Delta P(t)}{P(t-1)} \right] \tag{2.92}$$

where $P(t)$ is price at time t, $\Delta P(t)$ the change in price at time t, δ_1 a positive constant that reflects the impact of the absolute price level and δ_2 the diffusion price parameter. The authors explore whether the modified Generalized Bass model yields optimal policies that are more insightful and consistent with observed pricing patterns. They provide some numerical results.

Table 2.10 shows, among the diffusion studies incorporating marketing mix variables, some normative studies used to derive optimal marketing mix strategies. Although these studies (optimal control models of product diffusion) are analytically elegant, most of them do not provide empirical validation. Hence, we omit them and concentrate on those which show results from empirical studies in order to find the impact of marketing variables on the diffusion process of innovations; in fact, to show the role of marketing mix variables in understanding diffusion dynamics Table 2.11 summarizes the results obtained in these studies. In order to find common patterns within these results, we have divided Table 2.11 into studies that consider one, two or more marketing variables; and then into durable and frequently purchased products. The authors have considered different ways of incorporating marketing variables into the diffusion models, including separable and non-separable functions. The results obtained by the authors suggest that the validity of the alternative diffusion models can not be generalized; it depends on the type of products and even the type of brand.

Unfortunately, existing knowledge on the influence of marketing mix variables on diffusion is still "*uncertain and speculative*", as Simon and Sebastian (1987, p.455) pointed out almost two decades ago. Although there are plausible arguments that suggest that advertising and, especially, price (the marketing variables that have been most analyzed by researchers) may affect either the rate of adoption (the parameter of external and/or the parameter of internal influence), the size of the potential market, or both simultaneously, the empirical evidence is not conclusive. There is no unified framework to provide guidelines on which marketing variables to include or where and how to specify marketing variables within diffusion models (Dockner and Jorgensen, 1988a; Bottomley and Fildes, 1998; Bass, Jain and Krishnan, 2000).

To further emphasize the importance of incorporating marketing variables into the diffusion models we conclude this section with Bass (1980, p. 51) "*Although the model (Bass, 1969) has certain nice properties for forecasting purposes and is adequate for these purposes, it is incomplete in that the premises on which it is based deal only the social and behavioral influences on the timing of adoption. Economic forces such as price are ignored. From a forecasting viewpoint models with omitted variables are often superior to complete models in the sense that a forecast need not be required of exogenous variables in developing a forecast of an endogenous variable. Nevertheless, if the purpose of modeling is to enhance understanding of the relationship between social and economic forces, a model which integrates these elements is required*."

Table 2.11.
Results from studies on the impact of marketing variables on diffusion process.

	Function to incorporate the marketing variable into the model	Innovations	Adoption rate	Potential market[1]	Results[2]: The appropriate representation of the diffusion process is...
Price affects…					
Durables products					
Kalish and Lilien (1986a, 1986b)	$f(P(t)) = e^{-\delta P(t)}$ $P(t)$: price at time t, δ: a constant non-separable form is considered	Photovoltaic system	Not considered	Yes Price: -/s	MIM with a dynamic potential market and price. Price impacts the potential market.
Kamakura and Balasubramanian (1987)	$f(P(t)) = P(t)^{\delta}$ $P(t)$: price at time t, δ: a constant non-separable forms are considered	Refrigerators	Not considered	Yes Price: -/ns	Only one specification of the proposed model is used: MIM with a dynamic potential market, price and replacement. Price has no impact.
		Vacuum Cleaners	Not considered	Yes Price: -/ns	
		Toasters	Not considered	Yes Price: -/ns	
		Electric blankets	Not considered	Yes Price: -/ns	
Kamakura and Balasubramanian (1988)	$f(P(t)) = P(t)^{\delta}$ $P(t)$: price at time t, δ: a constant separable forms are considered	Toasters	No	No	EIM with a dynamic potential market
		Mixers	No	No	IIM with a dynamic potential market
		Blenders	No	No	IIM with a dynamic potential market
		Air conditioners	Yes Price: -/s	No	EIM with a dynamic potential market and price
		Refrigerators	Yes Price: -/s	No	MIM with a dynamic potential market and price
		Vacuum cleaners	Yes Price: -/s	No	MIM with a dynamic potential market and price

Table 2.11.
Results from studies on the impact of marketing variables on diffusion process (continued).

	Function to incorporate the marketing variable into the model	Innovations	Adoption rate	Potential market(1)	Results(2): The appropriate representation of the diffusion process is...
Price affects…					
Durables products					
Kamakura and Balasubramanian (1988) (continued)					There is no dominant specification in modeling the diffusion process for all the products; it depends on the product. General conclusions: Low priced products (Toasters, Mixers and Blenders) => Price has no impact. High priced products (Air conditioners, Refrigerators and Vacuum cleaners) => Price has impact.
Jain and Rao (1990)	Alternatives for $f(P(t))$: $f_1(P(t)) = P(t)^{\delta}$ $f_2(P(t)) = \frac{1}{\left(1+P\delta_1(t)^{\delta_2}\right)}$ $P(t)$: price at time t, δ_1 and δ_2: constants separable and non separable forms are considered	Room air conditioners	Yes Price: -/s	No	MIM with a fixed potential market and price ($f_1(t)$ and separable form)
		Clothes dryers	Yes Price: -/s	No	MIM with a fixed potential market and price ($f_1(t)$ and separable form)
		Color TVs	Yes Price: -/s	No	MIM with a fixed potential market and price ($f_1(t)$ and separable form)
		Can openers	No	No	MIM with a fixed potential market and price ($f_2(t)$ and non separable form)
					These results are consistent wit the empirical findings of Kamakura and Balasubramanian (1988)

Table 2.11.
Results from studies on the impact of marketing variables on diffusion process (continued).

	Function to incorporate the marketing variable into the model	Innovations	Adoption rate	Potential market[1]	Results[2]: The appropriate representation of the diffusion process is...
Price affects…					
Durables products					
Bhargava, Bhargava and Jain (1991)	Alternatives for $f(P(t))$: $f_1(P(t))=\left(\frac{P(t)}{P(0)}\right)^{\delta_1}$	Color TVs	No	Yes Price: +/s	MIM with a dynamic potential market and price ($f_1(t)$ and non separable form)
	$f_2(P(t))=\exp\left[\delta_2\left(1-\frac{P(t)}{P(0)}\right)\right]$		No	Yes Price: -/s	MIM with a dynamic potential market and price ($f_2(t)$ and non separable form)
	$P(t)$: inflation-adjusted price at time t, $P(0)$: price at time t=0, δ_1 and δ_2: constants		Yes Price: +/s	No	MIM with a fixed potential market and price ($f_1(t)$ and separable form)
	separable and non separable forms are considered		Yes Price: -/s	No	MIM with a fixed potential market and price ($f_2(t)$ and separable form)
					Price impacts the potential market and the adoption rate. These results are inconclusive.
Parker (1992)	$f_1(P(t))=P(t)^{\delta(t)}$	Blenders	No	No considered in the analysis given the results from Kamakura and Balasubramanian (1988) and Jain and Rao (1990)	IIM with a dynamic potential market, non-uniform influence and heterogeneous adoption.
	$P(t)$: price at time t $\delta(t)$: price elasticity function (constant, linear or quadratic)	Dishwashers	No		IIM with a dynamic potential market and non-uniform influence.
	separable and non-separable forms are considered	Microwave ovens	No		IIM with a fixed potential market.
		Steam irons	No		IIM with a dynamic potential market and non-uniform influence.
		Color TVs	No		IIM with a dynamic potential market and non-uniform influence.

Table 2.11.
Results from studies on the impact of marketing variables on diffusion process (continued).

	Function to incorporate the marketing variable into the model	Innovations	Adoption rate	Potential market[1]	Results[2]: The appropriate representation of the diffusion process is...
Price affects…					
Durables products					
Parker (1992) (continued)		Bed covers	Yes Price: constant -/s Price: constant -/s Price: constant -/s		Three models are retained: -IIM with a fixed potential market and non-uniform influence. Price affects adoption rate (separable form). -MIM with a fixed potential market. Price affects adoption rate (separable form). -MIM with a fixed potential market. Price affects external influence (non-separable form).
		Calculators	Yes Price: quadratic /s		MIM with a dynamic potential market and non-uniform influence. Price affects internal influence (non-separable form).
		Clothes dryers	Yes Price: quadratic /ns		MIM with a dynamic potential market and non-uniform influence. Price affects internal influence (non-separable form).
		Disposers	Yes Price: quadratic /s		MIM with a dynamic potential market and non-uniform influence. Price affects external influence (non-separable form).
		Freezers	Yes Price: quadratic /s		MIM with a dynamic potential market, non-uniform influence and heterogeneous adoption. Price affects internal influence (non-separable form).

Table 2.11.
Results from studies on the impact of marketing variables on diffusion process (continued).

	Function to incorporate the marketing variable into the model	Innovations	Adoption rate	Potential market[1]	Results[2]: The appropriate representation of the diffusion process is...
Price affects…					
Durables products					
Parker (1992) (continued)		Ironers	Yes Price: quadratic /ns Price: quadratic /s		Tow models are retained: -MIM with a dynamic potential market, non-uniform influence and heterogeneous adoption. Price affects external influence (non-separable form). -MIM with a dynamic potential market, non-uniform influence and heterogeneous adoption. Price affects internal influence (non-separable form).
		Rangers	Yes Price: linear /s		MIM with a dynamic potential market, and non-uniform influence. Price affects external influence (non-separable form).
		Built-in rangers	Yes Price: quadratic /s		IIM with a dynamic potential market, and non-uniform influence. Price affects adoption rate (separable form).

Table 2.11.
Results from studies on the impact of marketing variables on diffusion process (continued).

	Function to incorporate the marketing variable into the model	Innovations	Adoption rate	Potential market[1]	Results[2]: The appropriate representation of the diffusion process is...
Price affects…					
Durables products					
Parker (1992) (continued)		Refrigerators	Yes Price: quadratic /s		IIM with a dynamic potential market. Price affects adoption rate (separable form).
			Yes		Three models are retained:
			Price: linear /s		-MIM with a dynamic potential market and non-uniform influence. Price affects adoption rate (separable form).
			Price: constant -/s		-MIM with a dynamic potential market and non-uniform influence. Price affects external influence (non-separable form).
			Price: quadratic /s		-MIM with a dynamic potential market and non-uniform influence. Price affects internal influence (non-separable form).
		Black and white TVs	Yes Price: linear /s		IIM with a dynamic potential market, non-uniform influence and heterogeneous adoption. Price affects adoption rate (separable form).
		Water pulsators	Yes Price: quadratic /s		IIM with a dynamic potential market and non-uniform influence. Price affects adoption rate (separable form).

Table 2.11.
Results from studies on the impact of marketing variables on diffusion process (continued).

	Function to incorporate the marketing variable into the model	Innovations	Adoption rate	Potential market[1]	Results[2]: The appropriate representation of the diffusion process is...
Price affects…					
Durables products					
Parker (1992) (continued)					There is no a dominant specification in modeling the diffusion process for all the products; it depends on the product. In contrast to Kamakura and Balasubramanian (1988) and Jain and Rao (1990), price plays a role in the diffusion of some low priced products.
Mesak and Berg (1995)	$f(P(t)) = e^{-\delta P(t)}$ $P(t)$: price at time t δ: a constant separable and non-separable forms are considered	Dishwashers	No	Yes Price: -/s	-First purchases model: MIM with a dynamic potential market. Price affects potential market.
			Yes Price: -/s	Not considered	-Repeat purchases model: Price affects internal influence (non-separable form).
		Electric dryers	No	Yes Price: -/s	-First purchases model: MIM with a dynamic potential market. Price affects potential market.
			Yes Price: -/s	Not considered	-Repeat purchases model: Price affects internal influence (non-separable form).
		Disposers	No	Yes Price: -/s	-First purchases model: MIM with a dynamic potential market. Price affects potential market.
			No	Not considered	-Repeat purchases model: Price has no effect.

Table 2.11.
Results from studies on the impact of marketing variables on diffusion process (continued).

	Function to incorporate the marketing variable into the model	Innovations	Adoption rate	Potential market[1]	Results[2]: The appropriate representation of the diffusion process is...
Price affects…					
Durables products					
Mesak and Berg (1995) (continued)		Color TVs	No	Yes Price: -/s	-First purchases model: IIM with a dynamic potential market. Price affects potential market.
			No	Not considered	-Repeat purchases model: Price has no effect.
		Refrigerators	No	Yes Price: -/s	-First purchases model: IIM with a dynamic potential market. Price affects potential market.
			No	Not considered	-Repeat purchases model: Price has no effect.
		Freezers	No	No	-First purchases model: MIM with a fixed potential market.
			No	Not considered	-Repeat purchases model: Price has not effects.
		Rangers	No	No	-First purchases model: MIM with a fixed potential market.
			No	Not considered	-Repeat purchases model: Price has no effect.
		Black and white TVs	No	No	-First purchases model: MIM with fixed potential market.
			No	Not considered	-Repeat purchases model: Price has no effect.
		Air conditioners	No	No	-First purchases model: MIM with a fixed potential market.
			No	Not considered	-Repeat purchases model: Price has no effect.

Table 2.11.
Results from studies on the impact of marketing variables on diffusion process (continued).

	Function to incorporate the marketing variable into the model	Innovations	Adoption rate	Potential market[1]	Results[2]: The appropriate representation of the diffusion process is...
Price affects…					
Durables products					
Mesak and Berg (1995) (continued)					There is no dominant specification in modeling the diffusion process for all the products; it depends on the product. In contrast to Kamakura and Balasubramanian (1988) and Jain and Rao (1990), price does not play a role in the diffusion of all high priced products. Also, in contrast to those authors, price is likely to affect potential market for some high priced products.
Bottomley and Fildes (1998)	$f(P(t)) = P(t)^{\delta}$ $P(t)$: price at time t δ: a constant separable and non-separable forms are considered	-in the UK-			
		Color TVs	Yes Price: -/s	No	EIM with a dynamic potential market and price. Price affects external influence (separable form).
		Video cassette recorders	Yes Price: -/s	Yes Price: -/s	EIM with a dynamic potential market and price. Price affects external influence (separable form) and potential market.
		Microwave ovens	No	No	IIM with a dynamic potential market.
		Video-cameras (inc. camcorders)	No	No	IIM with a dynamic potential market.
		Compact disc players	No	No	IIM with a dynamic potential market.

Table 2.11.
Results from studies on the impact of marketing variables on diffusion process (continued).

	Function to incorporate the marketing variable into the model	Innovations	Adoption rate	Potential market[1]	Results[2]: The appropriate representation of the diffusion process is...
Price affects…					
Durables products					
Bottomley and Fildes (1998) (continued)		-in the USA-			
		Air conditioners	No	No	IIM with a dynamic potential market.
		Refrigerators	No	No	IIM with a dynamic potential market.
		Vacuum cleaners	No	No	EIM with a dynamic potential market.
		Blenders	No	No	MIM with a dynamic potential market.
		Mixers	Yes Price: -/s	No	EIM with a dynamic potential market and price. Price affects external influence (separable form)
		Toasters	No	No	MIM with a dynamic potential market. There is no dominant specification in modeling the diffusion process for all the products; it depends on the product.
Putsis (1998)	$f(P(t)) = \delta(t)P(t)$ $P(t)$: price at time t, $\delta(t)$: time-varying parameter non-separable forms are considered	Color TVs Video cassette recorders	Yes Price: (average) -/s	No	Putsis proposes a model different from classical diffusion model specifications and consider time varying parameters. Mixed influence and a dynamic potential market are considered.
Frequently purchased products					
None					

Table 2.11.
Results from studies on the impact of marketing variables on diffusion process (continued).

	Function to incorporate the marketing variable into the model	Innovations	Adoption rate	Potential market[1]	Results[2]: The appropriate representation of the diffusion process is...
Advertising[3] affects…					
Durables products					
Horsky and Simon (1983)	$f(A(t)) = \delta \ln(A(t))$ $A(t)$: advertising at time t, δ: a constant non-separable form is considered	Banking telephoning	Yes Advertising: +/s	Not considered	MIM with a fixed potential market. Advertising affects internal influence (non-separable form).
Simon and Sebastian (1987)	Alternatives for $f(A(t))$: $f_1(A(t)) = \delta_1 \ln(A(t-\tau))$ $\tau \geq 0$ $f_2(A(t)) = \sum_{\tau=0}^{T} \delta_{2\tau} \ln(A(t-\tau))$ $f_3(A(t)) = \delta_3 \ln(G(t))$ where $G(t) = \sum_{\tau=0}^{T} \delta_{3\tau} A(t-\tau)$ $A(t)$: advertising at time t, δ_1, δ_2 and δ_3: constants non-separable forms are considered	telephones	Yes Advertising: +/s	Not considered	MIM with a fixed potential market. Advertising affects internal influence ($f_3(t)$ and non-separable form).
Frequently purchased products					
Lilien, Rao and Kalish (1981)	$f_1(X(t)) = \delta_{11} X(t) + \delta_{12} X(t)^2$ and $f_2(X(t)) = -\delta_2 X_c(t)$ $X(t)$: promotional efforts (detailing) at time t $X_C(t)$: promotional efforts (detailing) of competing brands at time t, δ_{11}, δ_{12} and δ_2: constants non-separable forms are considered	2 prescription drugs	Yes Promotional efforts Drug nº1 δ_{11}: +/s δ_{12}: +/s δ_3: +/s	Not considered	MIM with a fixed potential market, promotional efforts (detailing) and repeat purchases. Promotional efforts (detailing) affect external and internal influence ($f_1(t)$ and $f_2(t)$, together, in a non-separable form). (Lilien, Rao and Kalish use results from Drug nº1 to analyze Drug nº2; so only results from Drug nº1 are shown)

Table 2.11.
Results from studies on the impact of marketing variables on diffusion process (continued).

	Function to incorporate the marketing variable into the model	Innovations	Adoption rate	Potential market[1]	Results[2]: The appropriate representation of the diffusion process is...
Advertising[3] affects…					
Frequently purchased products					
Rao and Yamada (1988)	Same model as Lilien, Rao and Kalish (1981). non-separable forms are considered	21 prescription drugs (results for 2 drugs are not shown)	Yes Promotional efforts δ_{11}: -14 out of 19 show: +/s -2 out of 19 show: +/ns -3 out of 19 show: -/s δ_{12}: -11 out of 19 show: +/s -5 out of 19 show: +/ns -3 out of 19 show: -/s δ_2: -11 out of 19 show: -/s -4 out of 19 show: -/ns -4 out of 19 show: -/s	Not considered	MIM with a fixed potential market, promotional efforts (detailing) and repeat purchases. Promotional efforts (detailing) affect external and internal influence ($f_1(t)$ and $f_2(t)$, together, in a non-separable form).
Hahn, Park, Krishnamurthi and Zoltners (1994)	Alternatives for $f(A(t))$: $f_1(X(t)) = \delta_1 \ln\left(\frac{X(t)}{X(t)+X_c(t)}\right)$ $f_2(X(t)) = \delta_2 \ln\left(X(t)\right)$ $X(t)$: promotional efforts (detailing and medical journal advertising) at time t $X_c(t)$: promotional efforts (detailing and medical journal advertising) of competing brands at time t δ_1 and δ_2: constants (one lag is considered in promotional efforts) non-separable forms are considered	21 prescription drugs	Yes Advertising -15 out of 21 show: +/s -6 out of 21 show: +/ns -16 out of 21 show: +/s -5 out of 21 show: +/ns	Not considered	Two specifications of the proposed model are used: -MIM with a fixed potential market, promotional efforts and repeat purchases. Promotional efforts affects external influence ($f_1(t)$, non-separable form). -MIM with a fixed potential market, promotional efforts and repeat purchases. Promotional efforts affects external influence ($f_2(t)$, non-separable form).

Table 2.11.
Results from studies on the impact of marketing variables on diffusion process (continued).

	Function to incorporate the marketing variable into the model	Innovations	Adoption rate	Potential market[1]	Results[2]: The appropriate representation of the diffusion process is...
Advertising[3] affects…					
Frequently purchased products					
Hahn, Park, Krishnamurthi and Zoltners (1994) (continued)					Promotional efforts are not considered to affect the repeat rate.
Distribution affects…					
Durable products					
Jones and Ritz (1991)	They use a system of equations to incorporate distribution	movies	Yes	Yes	Although Jones and Ritz propose a model that has the benefit of incorporating the effect of distribution into the diffusion process, their model does not provide better fit than the Bass model or the NUI model (Easingwood, Mahajan and Muller, 1983)
Frequently purchased products					
None					
Price and Advertising affects…					
Durable products					
Bass, Krishnan and Jain (1994)	$f(P(t),A(t)) = 1+\delta_1 \frac{P'(t)}{P(t)} + \delta_2 \frac{A'(t)}{A(t)}$ $P(t)$: price at time t $P'(t)$: change in price at time t $A(t)$: advertising at time t $A'(t)$: change in advertising at time t δ_1 and δ_2: constants separable forms are considered	Room air conditioners Clothes dryers Color TVs	Yes Price: -/s Advertising: +/s Yes Price: -/s Advertising: Not showed/ns Yes Price: -/s Advertising: +/s	Not considered Not considered Not considered	It is used only one specification of the proposed model: MIM with a fixed potential market, price and advertising. Price and advertising affect adoption rate (non-separable form).

Table 2.11.
Results from studies on the impact of marketing variables on diffusion process (continued).

	Function to incorporate the marketing variable into the model	Innovations	Adoption rate	Potential market[1]	Results[2]: The appropriate representation of the diffusion process is...
Price and Advertising affects…					
Frequently purchased products					
Parker and Gatignon (1994)	Alternatives for $f(P(t),A(t))$: $f_1(t) = P(t)^{\delta_1+\delta_2 B(t)} * A(t)^{\delta_3+\delta_4 B(t)}$ $f_2(t) = PM(t)^{\delta_1+\delta_2 B(t)} * AM(t)^{\delta_3+\delta_4 B(t)}$ where $PM(t) = \frac{P(t)}{\left(\frac{1}{B(t)}\right)\sum_{j=1}^{B(t)} P_j(t)}$ $AM(t) = \frac{A(t)}{\sum_{j=1}^{B(t)} A_j(t)}$ $P(t)$: price at time t, $A(t)$: advertising at time t, $B(t)$: the number of competing brands in the product category at time t, δ_1, δ_2, δ_3 and δ_4 are constants separable and non-separable forms are considered	5 brands of hair mousses		Not consider	
		Brand nº1	Yes Price: -/s Advertising: +/ns		MIM with a fixed potential market. Price and advertising affect external influence ($f_1(t)$, $B(t)$=0 and non-separable form).
		Brand nº2	Yes Price: -/s Advertising: +/s		MIM with a fixed potential market. Price and advertising affect external influence ($f_1(t)$ and non-separable form).
		Brand nº3	Yes Price: -/s Advertising: +/s Price: -/ns Advertising: +/ns		Two models are retained: -MIM with a fixed potential market. Price and advertising affect adoption rate ($f_2(t)$ and separable form). -MIM with a fixed potential market. Price and advertising affect internal influence ($f_2(t)$ and non-separable form).
		Brand nº4	Yes Price: -/s Advertising: +/s		MIM with a fixed potential market. Price and advertising affect internal influence ($f_1(t)$ and non-separable form).
		Brand nº5	Yes Price: +/s		MIM with a fixed potential market. Price affect external influence ($f_2(t)$, $B(t)$=0 and non-separable form).

Table 2.11.
Results from studies on the impact of marketing variables on diffusion process (continued).

	Function to incorporate the marketing variable into the model	Innovations	Adoption rate	Potential market[1]	Results[2]: The appropriate representation of the diffusion process is...
Price and Advertising affects…					
Frequently purchased products					
Parker and Gatignon (1994) (continued)					There is no common functional form to characterize all new brands entering into a new category.
Price, Advertising and Distribution affects…					
Durable products					
Mesak (1996)	$f_1(P(t)) = P(t)^{-\delta}, \quad \delta > 1$ $f_2(A(t)) = \sqrt{A(t)}$ $f_3(D(t) = D(t)$ $P(t)$: real (deflated) price index for the average monthly basic rate at time t, $A(t)$: real (deflated) index of advertising expenditures at time t, $D(t)$: distribution at time t δ: a constant separable and non-separable forms are considered	Cable TV	Yes Price: -/s Advertising: no parameter Distribution: no parameter		MIM with a dynamic potential market. Price affects internal influence (non-separable form), advertising affects adoption rate (separable form) and distribution affects potential market.
Frequently purchased products					
None					

(1) +: positive effect
-: negative effect
s: significant
ns: not significant
(2) MIM: Mixed influence diffusion model
EIM: External influence diffusion model
IIM: Internal influence diffusion model
(3) In this group we also consider other kinds of promotional activities such as detailing.

The extensions of the basic diffusion model shown in Section 2.4.2 help to better understand the diffusion pattern of innovations. The studies in this section reveal that there are a number of key issues that have a greater influence in some situations than in others and, hence, the basic diffusion models have to be adapted to include these issues. In this way, we improve their ability to describe or predict the diffusion processes of innovations. None of the extended models relaxes all nine discussed assumptions (see Appendix 2B, Table 2B). However, the studies reveal how, by relaxing one, two or three assumptions, the authors provide valuable improvements to the basic diffusion models. The results of these studies create a pool of knowledge on the diffusion processes of innovations, which is valuable to both researchers and managers. In the case of researchers, it motivates them to continue investigating. For example, they can apply the existing extended diffusion models to new situations and innovations in order to generalize their applicability and results; and they can also try to improve the existing models by overcoming their limitations and make them closer to real managerial problems. In the case of managers, this pool of knowledge is also interesting because it provides useful tools for marketing new products in different contexts and also provides useful information on the diffusion patterns of similar new products launched in the market in similar and/or different contexts. Although, there has been modeling research in marketing for several decades, much remains to be done as can be seen from this chapter. For instance, for management to benefit from the inclusion of marketing variables, more research on which variables to include and the form in which they should be included is needed. More research is also needed on diffusion at brand level since most diffusion models only focus on diffusion at the category level. In industries characterized by severe competition, "*brand managers are likely to pay equal, if not more, attention to understanding the sales growth at brand level*" (Krishnan, Bass and Kumar (2000, p. 269).

Appendix 2A. Specifications of the fundamental diffusion model: Analytical development

In this appendix, we present the analytical development of the three specifications of the fundamental diffusion model and provide the theoretical explanations of the dynamics of the diffusion process in terms of several general characteristics. Although other distribution functions may generate similar curves (for instance, cumulative normal generates an S-shape curve), the fundamental diffusion model and its specifications are based on the theory of the adoption and diffusion of innovations (Rogers, 1962, 1983, 1995; Robertson, 1971).

2A.1. The fundamental diffusion model: the external influence specification

The diffusion model of external influence (see Section 2.3.2, Equation (2.20)) is based on the assumption that the rate of diffusion depends solely on the distance remaining from the market saturation level; in other words, it depends on the number of potential adopters at time *t*.

External influence directly affects the innovative behavior of members of the social system. This kind of influence comes from both the intrinsic tendency of an individual (person or company) to innovate -also called innate innovativeness- and the promotional strategies found in the market[1]. Insofar as the model of external influence considers that the diffusion of an innovation is due exclusively to information coming from external sources, it does not accept any diffusion resulting from interaction between previous and potential adopters. The main limitation of this model is precisely that. Because of this, the use of this kind of diffusion model requires the assurance that the elements that influence the diffusion process are consistent with the formulation of the model. For example, this model can be appropriate for innovations that are neither socially remarkable nor complex, as they will not be influenced by personal communication between members of the social system and we can consider the social system to be isolated.

The main assumptions (Coleman, Katz and Menzel, 1957; Sharif and Ramanathan, 1981) that underlie this model are:

- the population of potential adopters is limited and remains constant through time;
- all members of the population eventually adopt the innovation;

[1] From a conceptual point of view, Mahajan and Peterson (1985) show that external influence represents the effect of one or more centralized, vertical, structured or formal channels of communication.

- the diffusion process arises from a source of constant influence, independent of the number of adopters;
- the impact of this constant and impersonal source is equal for all non-adopters.

Based on the above assumptions, the diffusion model takes the form shown by Equation (2.20) (Section 2.3.2):

$$\frac{dN(t)}{dt} = a\left[M - N(t)\right].$$

This equation shows that a constant exogenous source of influence reaches a fixed proportion of the population at any given moment in time. The constant *a*, which is defined as a parameter of external influence, expresses the probability of a randomly chosen individual being reached by this source of influence. Therefore, in every instant *t*, of the *aM* individuals reached, $N(t)/M$ are adopters:

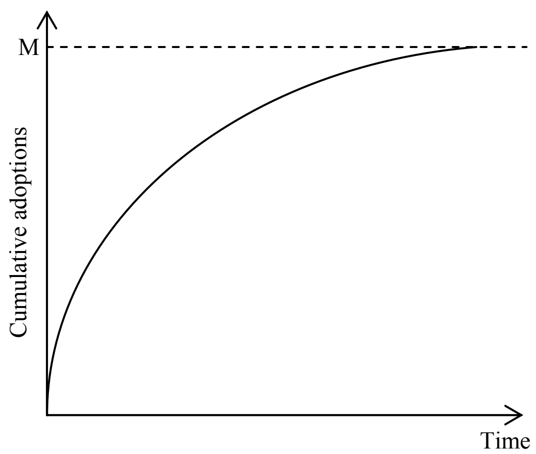
$$\frac{dN(t)}{dt} = aM\left[1 - \frac{N(t)}{M}\right]. \tag{2A.1}$$

Integrating this first order linear differential equation and using the condition limit $N(t{=}t_0){=}N_0$, we obtain the cumulative distribution of adopters, $N(t)$:

$$N(t) = M\left[1 - e^{-at}\right] \quad \text{or} \quad \ln\left[\frac{1}{1 - \dfrac{N(t)}{M}}\right] = at \tag{2A.2}$$

Figure 2A.1 shows how the model of external influence is a modified exponential function or decreasing exponential function where *M* denotes the level of saturation and $N(t)$ grows at a constant diminishing rate.

Figure 2A.1.
Modified exponential function: Cumulative adoptions



Pioneering works in the use of the diffusion model of external influence are those of Fourt and Woodlock (1960), Coleman, Katz and Menzel (1966) and Hamblin, Jacobsen and Miller (1973). Fourt and Woodlock (1960) demonstrate that sales predictions for certain consumer products require the application of a modified exponential curve. Coleman, Katz and Menzel (1966) investigate the diffusion of a new medicine among a group of doctors. Hamblin, Jacobsen and Miller (1973) base their study on the analyses of diffusion patterns of labor strikes and political assassinations in various countries.

2A.2. The fundamental diffusion model: the internal influence specification

In the diffusion model of internal influence (see Section 2.3.2, Equation (2.21)), the rate of diffusion at a given point in time t is proportional to both the distance remaining from a predetermined market saturation level, $[M\text{-}N(t)]$, and the level of diffusion reached, $N(t)$. The internal influence model does not consider the intrinsic tendency of an individual to adopt or impersonal sources of information to be relevant at the moment of deciding to adopt and, therefore, considers that they do not significantly affect the diffusion process. The model is based on the existence of communication between members of the social system (social interaction, represented in the model by the product of previous and potential adopters, $N(t)[M\text{-}N(t)]$). It has its origins in the contagionist paradigm[2], in that diffusion only comes about through personal contact between previous and potential adopters. In this type of epidemiological model we can clearly observe how the probability of adoption increases in line with increases in the number of adopters in the social system; this is a logical process as the greater the number of previous adopters, the more information there will be in the market on the characteristics, advantages and previous adopters' experience of the innovation, which would reduce the risk aversion of potential adopters and favor the decision to adopt[3].

This model is based on the following assumptions (Dodds, 1973; Sharif and Ramanathan, 1981):

- the population of potential adopters is limited and remains constant throughout time;
- all members of the population eventually adopt the innovation;
- the population mixes homogenously;

[2] This is analogous with the models of epidemics (Bailey, 1957), biology (Pearl, 1925; Lotka, 1956) or ecology (Pielou, 1969).

[3] Although there is also the possibility of a negative interaction, the majority of authors lean towards sole consideration of the positive component of interpersonal communication.

- all adopters are imitators and only adopt after having seen others use the innovation;
- the rate of adoption does not only depend on the number of previous adopters but also on the maximum number of potential adopters that still have not adopted;
- the probability of two individuals making contact is equal for any two individuals.

Based on the above assumptions, the diffusion model takes the form shown by Equation (2.21) (Section 2.3.2):

$$\frac{dN(t)}{dt} = bN(t)\left[M - N(t)\right].$$

This equation represents a diffusion model of pure imitation and parameter b is defined as a parameter of internal influence or an index of potential adopters' imitation of previous adopters[4].

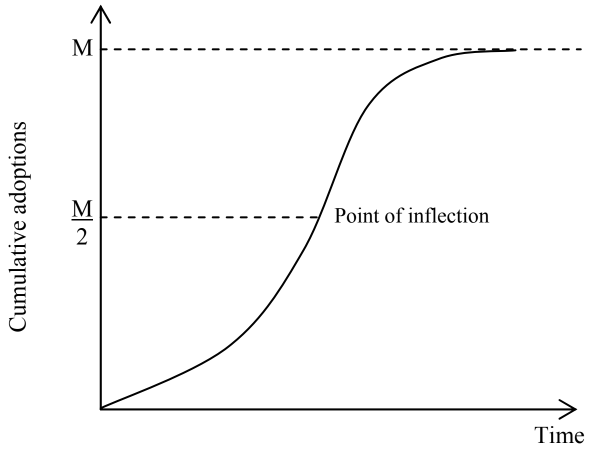
Integrating this first order linear differential equation (Bernouilli type) and using condition limit $N(t{=}t_0){=}N_0 \geq 1$, we obtain the cumulative distribution of adopters, $N(t)$:

$$N(t) = \frac{M}{1 + \dfrac{(M - N_0)}{N_0} e^{-bM(t-t_0)}} \quad \text{or} \quad \ln\left[\frac{N(t)}{M - N(t)}\right] = \ln\left[\frac{N_0}{M - N_0}\right] + bM(t - t_0) \quad (2A.3)$$

Equation (2A.3) is a logistic function where M denotes the level of saturation; see Figure 2A.2. The concept of logistic function implies that the cumulative growth of a product in a market over a period of time presents a characteristic sigmoidal or S-shaped curve, which is symmetrical with respect to the point of inflexion (0.5M).

[4] Gray (1973) denominates b as the parameter of diffusion through interaction. Mahajan and Peterson (1985), from a conceptual point of view, consider parameter b as a representative of the effect of one or more decentralized, horizontal, destructured or informal communication channels.

Figure 2A.2.
Logistic function: Cumulative adoptions



Pioneering and best known works on the application of the diffusion model of internal influence are those of Griliches (1957) and Mansfield (1961). Griliches (1957) explains differences in the use of hybrid corn among farmers from various geographical regions of the United States of America. Mansfield (1961), working with data from various industries and innovations, studies the process through which new technology substitutes established technology and analyses the factors that affect the speed with which an innovation spreads to different companies.

The model of internal influence is related to models of technological substitution[5], such as those proposed by Fisher and Pry (1971) and Blackman (1972). Considering the spread of a given technology at moment t, $h(t)=N(t)/M$, and complete market saturation, $\bar{H}=M/M=1$, and $H(t=t_0)=H_0=1/2$, the internal influence diffusion model takes the form:

$$\frac{dH(t)}{dt}=b' H(t)\left[\bar{H}(t)-H(t)\right]. \tag{2A.4}$$

Integrating the above equation and substituting $b'=2\delta$ we obtain the model suggested by Fisher and Pry (1971):

[5] For a comprehensive review of technological substitution and successive product generations see Norton and Bass (1987), Kumar and Kumar (1992), Jiménez (1996) and Bayus, Kim and Shocker (2000).

$$H(t)=\frac{1}{1+e^{-2\delta(t-t_0)}} \quad \text{or} \quad \frac{H(t)}{1-H(t)}=e^{2\delta(t-t_0)} \tag{2A.5}$$

$$\ln\left[\frac{H(t)}{\bar{H}(t)-H(t)}\right]=\ln\left[\frac{H_0}{\bar{H}-H_0}\right]+b'\bar{H}(t-t_0). \tag{2A.6}$$

Calling $c_1=\ln\left[\frac{H_0}{\bar{H}-H_0}\right]-b'\bar{H}t_0$ and $c_2=b'\bar{H}$, we arrive at the model of technological substitution of Blackman (1972):

$$\ln\left[\frac{H(t)}{\bar{H}(t)-H(t)}\right]=c_1+c_2t. \tag{2A.7}$$

The main difference between the previous two models is that Fisher and Pry specify the values of parameter $b'=2\delta$ and $\bar{H}=1$.

The well-known Gompertz diffusion model is also directly related to the internal influence model; although this model maintains the elongated S-shape characteristic of diffusion processes, the point of inflexion is reached before reaching the half saturation point as happens with the logistic function. The Gompertz reaches its peak rate earlier at 37 percent ($N(t)=e^{-1}M=0.368M$). The Gompertz function is expressed:

$$\frac{d(N(t))}{dt}=bN(t)\left[\ln M-\ln N(t)\right] \tag{2A.8}$$

where $N(t=t_0)=N_0$ and integrating the above function we obtain the cumulative distribution of adopters of the Gompertz function:

$$N(t)=M\exp\left[-\left(\ln\frac{M}{N_0}\right)\exp\left[-b(t-t_0)\right]\right] \text{ or } \ln\left[\frac{\ln M-\ln N(t)}{\ln M-\ln N_0}\right]=-b(t-t_0). \tag{2A.9}$$

2A.3. The fundamental diffusion model: the mixed influence specification

The diffusion model of mixed influence (see Section 2.3.2, Equation (2.22)) considers that both types of influence are present in the decision to adopt an innovation, i.e. both the influence of the intrinsic tendency of an individual to adopt and the impersonal communication -*Model of external influence*-, and the influence of previous adopters on potential adopters -*Model of internal influence*-. This is the most widely used model and the most general specification of the fundamental diffusion model[6]. Although the model of mixed influence incorporates both external and internal influence, it does not imply that it is always the best model to represent the diffusion process of any innovation[7]. Logically, in some situations the dominant influence could come from sources other than adopters of the innovation, whereas in other situations the dominant force comes from interaction between members of the social system[8].

Insofar as this model groups together the external and internal specifications, the main assumptions established for them are valid in the mixed or generalized context[9]. The following first-order differential equation (Section 2.3.2, Equation (2.22)) captures the diffusion dynamics of the diffusion model of mixed influence:

$$\frac{dN(t)}{dt} = \left(a + bN(t)\right)\left[M - N(t)\right].$$

Integrating this equation we obtain the following cumulative distribution of adopters:

$$N(t) = \frac{M - \dfrac{a(M - N_0)}{(a + bN_0)} \exp\left[-\left(a + bM\right)(t - t_0)\right]}{1 + \dfrac{b(M - N_0)}{(a + bN_0)} \exp\left[-\left(a + bM\right)(t - t_0)\right]} \tag{2A.10}$$

where $N(t{=}t_0){=}N_0$. The cumulative distribution of adopters gives us a generalized logistic curve whose shape is determined by parameters *a* and *b*.

Bass (1969) pioneered the introduction of diffusion models into the marketing literature. He suggests that the adoption process of a new durable consumer product is similar to the spread of an epidemic, in which people who have not adopted the innovation are "infected" by those who have (previous adopters) and are influenced by external sources like advertising. Bass uses his model to analyze

[6] The communication process in a social system is based on the communication hypotheses formulated by Lazarsfeld, Berelson and Gaudet (1948). According to these authors a message from the mass media does not affect the majority of intended receivers, but first reaches a group who then influence the other individuals within the social system.

[7] Authors like Kamakura and Balasubramanian (1988), Parker (1993), and Bottomley and Fildes (1998) in the context of consumer durable products, and Parker and Gatignon (1994) in the context of common consumer products examine the importance of external and internal influence in the diffusion process of some products. Their results show that the mixed influence diffusion model is not necessarily the most appropriate for every product.

[8] Lekvall and Wahlbin (1973) affirm that both theoretical and empirical considerations indicate that the nature of the innovation is a crucial factor when explaining the greater or lesser importance of the two influence types on the diffusion process.

[9] This model is also known as the generalized diffusion model (Mahajan and Schoeman, 1977; Sharif and Ramanathan, 1981).

the diffusion of consumer durables (electric refrigerators, home freezers, black and white televisions, water softeners, room air conditioners, clothes dryers, power lawnmowers, electric bed coverings, automatic coffee makers, steam irons and recorder players) and obtains very good results on sales predictions for these products. There are many authors who have subsequently applied the Bass model of mixed influence diffusion, widening the field of application to other innovations in various countries and always obtaining good results. In fact, a considerable number of articles and models stems from the work of Bass[10].

2A.3.1.The analogous discrete

Researchers use observed data on cumulative adoptions, $N(t)$, to compute the empirical number of adopters in the time interval (t, t-1):

$$x(t) = N(t) - N(t-1). \tag{2A.11}$$

Given that $F(t)=N(t)/M$, the fraction of the potential adopters who adopt the product by time t, expression (2A.11) can be expressed as:

$$x(t) = M\left[F(t) - F(t-1)\right] \tag{2A.12}$$

where M is the potential market and $F(t)$ the cumulative distribution function (or the fraction of potential adopters that has adopted the product by time t). Given the expression of the Bass model

$$f(t) = \frac{dF(t)}{dt} = \left(\beta_1 + \beta_2 F(t)\right)\left[1 - F(t)\right] \tag{2A.13}$$

where $f(t)$ is the density function of time to adoption and β_1 and β_2 are parameters, and integrating (2A.13) with $F(t=0)=0$, we have

$$F(t) = \frac{1 - e^{-(\beta_1+\beta_2)t}}{1 + \dfrac{\beta_2}{\beta_1} e^{-(\beta_1+\beta_2)t}}. \tag{2A.14}$$

Following the Srinivasan and Mason's (1986) estimation procedure[11], the estimation equation for the mixed influence diffusion model is given by

[10] See Sultan, Farley and Lehmann (1990) for empirical applications of the Bass model.

[11] Jain and Rao (1990) suggest another approach, however Van den Bulte and Lilien (1997) point out that as the Srinivasan and Mason's approach is less complex, the tendency of the estimates to vary is smaller as one extends the data set. Bemmaor and Lee (2002, p.218) also show that "*more complex models can result in large changes in the parameter estimates as the number of data points increases*".

$$x(t) = M\left[F(t) - F(t-1)\right] + \mu(t) =$$
$$M\left[\frac{1-e^{-(\beta_1+\beta_2)t}}{1+\frac{\beta_2}{\beta_1}e^{-(\beta_1+\beta_2)t}} - \frac{1-e^{-(\beta_1+\beta_2)(t-1)}}{1+\frac{\beta_2}{\beta_1}e^{-(\beta_1+\beta_2)(t-1)}}\right] + \mu(t). \tag{2A.15}$$

where M, β_1, and β_2 are parameters and $\mu(t)$ is an additive i.i.d. random term.

Schmittlein and Mahajan (1982) point out that the estimation of a model from the discreet form introduces a temporal interval bias, but Mahajan, Muller and Bass (1993) point out that the estimations of the parameters do not differ in a significant way among the methods of estimation that control or ignore such bias.

The advantage the fundamental diffusion model of external, internal or mixed influence has over some of its extensions is that its cumulative distribution function ($F(t)$) takes a closed-form expression. This means that the number of adopters ($N(t)$=$MF(t)$) can be expressed as a function of time alone. Diffusion models in which this is not possible are estimated directly from their original expressions.

Appendix 2B. Assumptions behind the diffusion modeling: Summary tables

Table 2B
Assumptions relaxed by authors

		Assumption[1]								
Authors	Year	1	2	3	4	5	6	7	8	9
Cassetti and Semple	1969					X				
Robinson and Lakhani	1975			X						X
Midgley	1976	X								
Haynes, Mahajan and White	1977					X				
Dodson and Muller	1978	X	X		X		X			X
Mahajan and Peterson	1978		X							
Peterson and Mahajan	1978						X			
Mahajan and Peterson	1979					X				
Mahajan, Peterson, Jain and Malhotra	1979		X							
Bass	1980			X						X
Dolan and Jeuland	1981			X	X					X
Easingwood, Mahajan and Muller	1981			X						
Jeuland	1981a	X								
Lawrence and Lawton	1981				X					
Lilien, Rao and Kalish	1981			X	X		X			X
Sharif and Ramanathan	1981		X							
Bass and Bultez	1982			X						X
Feichtinger	1982		X							X
Jeuland and Dolan	1982			X	X					X
Mahajan and Muller	1982	X			X					
Sharif and Ramanathan	1982	X								
Easingwood, Mahajan and Muller	1983			X						
Horsky and Simon	1983			X						X
Jorgensen	1983		X							X
Kalish	1983			X						X
Mahajan, Wind and Sharma	1983				X					
Teng and Thompson	1983			X			X			X
De Palma, Droesbeke and Lefevre	1984		X	X				X		X
Mahajan, Muller and Kerin	1984	X								
Thompson and Teng	1984			X			X			X
Kalish	1985	X	X	X				X		X
Olson and Choi	1985		X		X					
Rao and Bass	1985			X			X			X
Srivastava, Mahajan, Ranaswami and Cherian	1985			X				X		
Eliashberg and Jeuland	1986			X			X			X
Kalish and Lilien	1986a,b		X	X				X		X
Bayus	1987	X	X		X		X			
Gore and Lavaraj	1987	X				X				
Kamakura and Balasubramanian	1987		X		X					X
Simon and Sebastian	1987			X						X

Table 2B
Assumptions relaxed by authors (continued)

		Assumption(1)								
Authors	Year	1	2	3	4	5	6	7	8	9
Dockner and Jorgensen	1988a			X						X
Dockner and Jorgensen	1988b			X			X			X
Horsky and Mate	1988			X			X			X
Kamakura and Balasubramanian	1988		X	X						X
Rao and Yamada	1988			X	X		X			X
Tanny and Derzko	1988	X								
Gatignon, Eliashberg and Robertson	1989					X				
Horsky	1990		X							X
Jain and Rao	1990		X	X						X
Bhargava, Bhargava and Jain	1991		X	X						X
Jain, Mahajan and Muller	1991	X							X	
Jones and Ritz	1991		X							X
Mahajan and Muller	1991						X			X
Dockner and Jorgensen	1992			X			X			X
Parker	1992	X	X	X						X
Bucklin and Sengupta	1993						X			
Mahajan, Sharma and Buzzell	1993						X			
Martins and Nascimento	1993		X		X		X			X
Parker	1993	X	X	X						
Bass, Krishnan and Jain	1994		X	X						X
Hahn, Park, Krishnamurthi and Zoltners	1994			X	X		X			X
Mahajan and Muller	1994					X				
Parker and Gatignon	1994			X			X			X
Givon, Mahajan and Muller	1995						X			
Jain and Maesincee	1995					X				
Jain, Mahajan and Muller	1995			X						X
Kalish, Mahajan and Muller	1995					X	X			
Mesak and Berg	1995		X	X	X					X
Eliashberg and Helsen	1996					X				
Ganesh and Kumar	1996					X				
Mesak	1996		X	X						X
Ganesh, Kumar and Subramanian	1997					X				
Givon, Mahajan and Muller	1997						X			
Putsis, Balasubramanian, Kaplan and Sen	1997					X				
Bottomley and Fildes	1998		X	X						X
Dekimpe, Parker and Echambadi	1998					X				
El Ouardighi and Tapiero	1998							X		
Kumar, Ganesh and Echambadi	1998					X				
Putsis	1998			X	X					X
Krishnan, Bass and Jain	1999			X						X
Dekimpe, Parker and Sarvary	2000b,c					X				
Kim, Chang and Shocker	2000						X			

Table 2B
Assumptions relaxed by authors (continued)

Authors	Year	Assumption(1) 1	2	3	4	5	6	7	8	9
Krishnan, Bass and Kumar	2000						X			
Bemmaor and Lee	2002	X								
Ho, Savin and Terwiesch	2002	X							X	
Kumar and Krishnan	2002					X				
Talukdar, Sudhir and Ainslie	2002					X				
Allaway, Berkowitz and D'Souza	2003					X				
Kumar and Swaminathan	2003								X	
Steffens	2003				X					
Swami and Khairnar	2003			X					X	
Chapter 4	*2004*		*X*	*X*						*X*
Chapter 5	*2004*	*X*	*X*	*X*						
Chapter 6	*2004*			*X*	*X*		*X*			*X*

(1) Assumptions:
1: The diffusion process is a binary process and population is homogeneous.
2: The size of the adopter population does not change.
3: The parameters of external and internal influence remain constant.
4: Only one adoption per adopter is allowed.
5: Geographical frontiers do not vary.
6: The innovation is diffused in isolation.
7: The characteristics of an innovation and its perception do not alter.
8: There are no supply restrictions.
9: The impact of the marketing variables used to diffuse an innovation is implicitly captured by the model parameters.

Chapter 3

An introduction to three empirical applications

In this short chapter we introduce the three empirical applications we carry out in this study. We also justify why we develop these models and their applications.

The applications that we present in the following sections are built on the traditional Bass model. The Bass model is the most parsimonious aggregated diffusion model suggested in marketing literature (Parker, 1994). The Bass model is the foundation for many articles in marketing because, since it was published, several hundred articles have been written (Mahajan, Muller and Bass, 1990, 1993; Mahajan, Muller and Wind, 2000) on the applications and extensions of the model (Sultan, Farley and Lehmann, 1990). Moreover, the Bass model has been the basis for the formulation of *empirical generalizations* in marketing (Bass, 1993, 1995). Despite this, it has its shortcomings because it is based on number of rather restrictive assumptions (see Section 2.4).

The assumptions of the Bass model mean that it lacks important details that do not allow the analyses of the diffusion process of certain innovations in certain situations. For example, an extended diffusion model is needed when researchers are interested in investigating the role of price in the diffusion process of electrical durable innovations. In this situation, researchers need a diffusion model that accounts for the effect of price. Furthermore, previous research has found that for this kind of innovation, the potential market varies with the number of households with electricity. Hence, the extended model should also incorporate a dynamic potential market to account for this fact. In this respect, research on relaxing some of the assumptions of the classical diffusion models helps new research to provide powerful tools for investigating the temporal diffusion process of any innovation in any situation. We proceed in this direction. The topics that we investigate address some of the shortcomings of the Bass model (see Table 3.1). The applications show different models and are applied in different contexts.

Diffusion of movies in neighboring Mediterranean countries (Chapter 4)

The present study has two objectives. First, we extend basic diffusion models to incorporate distribution into the models, which is a rarely incorporated marketing variable. Then, we analyze the *country* and *time effects* in the diffusion processes of a number of new products in different Mediterranean European countries. The analysis of these kinds of effects can reveal differences or likenesses in the diffusion patterns among countries, allowing managers to design appropriate (similar or different) marketing plans when they are thinking of commercializing the same innovation in those countries. Two well-known Bass-type models are used to incorporate distribution as a decision variable and some statistical tests and a regression analysis are developed to detect the *country* and the *time effects*. The empirical application is carried out on a group of new movies shown in Spain, France and Italy during the period 1997-1999.

The Bass model is based on nine assumptions, as has been discussed extensively in Chapter 2. In Chapter 4 we relax assumptions 2, 3 and 9, because:

- we allow the potential market to be dynamic. In our model we assume that distribution can affect the size of the potential market (assumption 2).
- we assume that the parameters of external and internal influence vary over the diffusion process of the innovation. More explicitly: we assume that distribution affects the adoption rate (assumption 3).
- we explicitly consider a marketing variable: distribution (assumption 9).

Although we consider different countries, we do not relax assumption 5. As with other authors (see Section 2.4.2.5), we use a diffusion model to analyze differences in the diffusion processes of the same group of innovations in different countries, but we do not incorporate any modification in the model to account for the specific characteristics of each geographical area. The analysis of distribution is very interesting given the relevance of this marketing variable in the commercialization of any product in the marketplace, and given the low number of diffusion studies that consider this marketing variable (see Section 2.4, Table 2.10). Furthermore, the analysis of movies in different Mediterranean countries (France, Italy and Spain) allows us to distinguish whether there are differences in the diffusion processes among these countries because of some specific country factors -"country effect"- and/or because of the moment of the product introduction in the market -"time effect"-.

Diffusion of franchising in Spain (Chapter 5)

In this study, we consider the diffusion of an organizational innovation, namely franchising, by firms in Spain during the period 1974-1999. We analyze the diffusion of franchising among firms as an organizational innovation from the point of view of the franchisors (i.e. inter-firm diffusion). The adoption of this system of commercialization has extreme consequences for the adopting organization (the franchisor). We apply well known diffusion models to detect how many firms are influenced by firms that have adopted the franchising concept ("imitators") and how many firms are not influenced by the timing of the adoption by other firms ("innovators"). We develop a four step approach to select the most appropriate diffusion model. After visual analysis of the data, we test whether the adoption follows a purely random process or whether firms imitate the adoption of the franchising concept. In the third step we compare some nested and non-nested models and the final selection is based on stability and predictive validation criteria.

Chapter 5 focuses on an organizational innovation, franchising; where the decision maker is not the consumer, but the firm. This chapter highlights the usefulness of diffusion models in analyzing diffusion processes of organizational innovations, which had been in doubt with the work of Mahajan, Sharma and Bettis (1988). We relax in this second application the first three assumptions of the Bass model. We relax assumption 1 and consider the possibility of a heterogeneous population of adopters through the incorporation of a new parameter into some of the models. We assume that the potential market depends on the number of Spanish firms available in the marketplace during the diffusion process of the innovation (assumption 2). And, assumption 3 is relaxed by considering a non-uniform parameter of internal influence in some of the diffusion models.

Diffusion of prescription drugs in the United States of America (Chapter 6)

In this study, we employ diffusion modeling to investigate longitudinal and cross-sectional effects of marketing expenditures on the diffusion of new pharmaceuticals. Although we focus on a certain product category characterized by a large number of introductions (new drugs) during the observational period, we also apply the same analyses to two other categories, one with close similar characteristics and another quite different to the previous category. We extend previous research on trial-repeat diffusion models by proposing a family of diffusion models that allows us: i) to accommodate own and competitors' different marketing instruments, and ii) to detect the appropriate allocation for marketing instruments in the trial rate, instead of considering *a priori* that marketing instruments affect it through the external influence, as previous studies do. After selecting the most appropriate trial-repeat diffusion model, we investigate cross-sectional effects of marketing instruments on both the trial and the repeat rate of the diffusion processes of the new pharmaceutical products. The cross-sectional analysis allows us to study whether marketing expenditures both have an informative and persuasive influence on the diffusion processes. The empirical application is carried out by using US data on the "rhinitis", "asthma" and "osteoarthritis-rheumatoid-arthritis" categories of prescription drugs in the observational period 1993-2000.

In Chapter 6 we address the diffusion of prescription drugs, i.e. the diffusion of frequently purchased consumer products. The lack of attention to model this kind of goods is due to the difficulty of both modeling repeat purchases and finding appropriate databases in which sales are divided into first and repeat purchases. Although we consider consumer products, it is not the consumers who are the decision makers but the doctors who prescribe the prescription drugs. In this chapter four assumptions behind the Bass model are relaxed. Assumption 3: we assume that marketing variables affect external and/on internal influence over the diffusion process. Assumption 4: we explicitly incorporate repeat purchases into the diffusion model. Assumption 6: we consider the effect of competitive variables on the diffusion process. Assumption 9: we incorporate marketing variables, such as detailing, medical journal advertising, physician meetings and direct-to-consumer advertising.

Table 3.1.
Characteristics of the empirical applications

	Chapter 4	Chapter 5	Chapter 6
Innovation	Entertainment and experience consumer products: Movies	Organizational: Franchising	Frequently purchased consumer product: Prescription drugs
Decision maker	Consumers	Firms	Doctors
Assumptions relaxed	<u>Assumption 2</u> Dynamic potential market <u>Assumption 3</u> Varying parameters of external and internal influence (using separable function) <u>Assumption 9</u> Marketing variables: distribution	<u>Assumption 1</u> Heterogeneous adopter population <u>Assumption 2</u> Dynamic potential market <u>Assumption 3</u> Varying parameter of internal influence (using non-separable function)	<u>Assumption 3</u> Varying parameter of external and/or internal influence (using separable and non-separable function) <u>Assumption 4</u> Repeat purchases <u>Assumption 6</u> Competition context <u>Assumption 9</u> Marketing variables: detailing, medical journal advertising, physician meetings, and direct-to-consumer advertising
Country	France, Italy and Spain	Spain	United States of America

In the chapter that follows the three applications addressed in the thesis, we summarize their contributions and we discuss the limitations of these models.

Chapter 4

Diffusion of movies in neighboring Mediterranean countries[1]

4.1. Introduction

For firms operating in a global environment, it is useful to understand to what extent adoptions in one country may affect adoptions in another country (Putsis et al., 1997). The knowledge and understanding of the diffusion process of a new product in a specific region or country is obviously of paramount relevance and has clear implications to managers planning to introduce the new product (or another of similar characteristics) in another region or country. Researchers, such as Gatignon, Eliashberg and Robertson (1989), Takada and Jain (1991), Helsen, Jedidi and DeSarbo (1993), Redmond (1994), Kumar, Ganesh and Echambadi (1998) and Putsis et al. (1997) have been interested in these geographical aspects and have examined the differences in the diffusion parameters for durable consumer products among different countries. Differences in the adoption processes are explained by specific factors from each country that are beyond companies' control and that can be grouped into two effects:

- the *country effect*, which considers factors such as geographical consumer mobility, cosmopolitanism, the role of women in the labor force, cultural level, prosperity and life-style, and
- the *time effect*, which considers the time lag between introductions among countries.

A *country effect* means that individual country characteristics influence the diffusion processes of innovations. A *time effect* reveals how the time lag between the introduction of an innovation in the pioneer (or lead) country and subsequent countries (or lag countries) affects the diffusion patterns in the latter countries.

The present study has two objectives. First, we extend basic diffusion models to incorporate distribution, which is a rarely incorporated marketing variable. Then,

[1] This chapter is based on the study of Ruiz and Mas (2001).

we analyze the *country* and *time effects* in the diffusion processes of a number of new products in different European countries. The empirical application is carried out on a group of new movies shown in Spain, France and Italy during the period 1997-1999. In summary, the results show that the Generalized Bass model extended to distribution is, in general terms, revealed as the preferred diffusion model for three countries, Spain, France and Italy. The results also show that there is a *country effect* between Spain and France and between Italy and France, although not between Spain and Italy. However, there is insufficient empirical evidence to show the role played by the *time effect*.

We study the diffusion of new movies. We believe that this is interesting for the following three reasons. First, we extend the application of Bass-type diffusion models to include consumer products other than the commonly studied durables. Second, we study the crucial role that retailers (or exhibitors) play in the diffusion process of movies. The extent to which consumers adopt movies depends on their availability; in other words, on the number of screens showing the movies. Third, although the motion picture industry has received increasing attention from marketing scholars as well as economists in recent years, there has been little emphasis on non-U.S. markets (exceptions are Walls (1997), Neelameghan and Chintagunta (1999) and Elberse and Eliashberg (2003)).

The remainder of this study is organized as follows. We start with a review of relevant literature[2]. We then propose extensions to the Bass model by explicitly incorporating distribution as a decision variable. We then develop the data analysis with movie data from Spain, France and Italy, and examine *country* and *time effects*. Finally, we present the conclusions.

4.2. General background

Although the Bass model has been considered an empirical marketing generalization (Mahajan, Muller and Bass, 1995), it has been criticized for its simplification of reality. Its extensions incorporate different variables in an explicit way, especially those explicitly based on marketing decisions (see Chapter 2, Section 2.4.2.9). The explicit incorporation of marketing variables not only gives the model

[2] Although there is existing literature on forecasting the performance of new movies, (Sawhney and Eliashberg, 1996; Neelameghan and Chintagunta, 1999; Neelameghan and Jain, 1999; Eliashberg, Jonker, Sawhney and Wierenga, 2000) it is not based on Bass-type models, and hence we do not discuss it here

greater realism but also contributes to better business management by considering the possibility of altering the diffusion process through marketing control.

Even though the importance of analyzing distribution as one aspect of the commercialization process has long been recognized (Mahajan, Muller and Bass, 1990, 1993; Mahajan, Muller and Wind, 2000), this marketing variable has received relatively little empirical attention in marketing literature, due mainly to the lack of available data. Furthermore, researchers do not agree on the type of model that should be used to evaluate the impact of distribution on the diffusion process. Jones and Ritz (1991) take the three-stage diffusion process as their starting point. They distinguish between the untapped market, the effective potential market and the current market (Mahajan and Muller, 1979). They consider a system of equations in which two parallel diffusion processes interact, one through retailers (producer to retailers) and the other through consumers (retailers to consumers), since consumers cannot adopt the product if retailers do not offer it. Their system presents the retailers' diffusion process with a modified Bass model (mixed influence diffusion model), and that of consumers with a constant transfer rate (diffusion model of external influence). They link both processes by assuming that each adopter-retailer increases the pool of potential adopter-consumers by a fixed amount. Jones and Ritz (1991) conclude, however, that their model achieves a lower degree of fit than other models that only reflect a single consumer process (producer to consumers) and that do not incorporate marketing variables, such as the Bass model and the NUI model (Easingwood, Mahajan and Muller, 1983).

Mesak (1996) applies a single-equation model (mixed influence diffusion model) that reflects a single consumer diffusion process. His proposal introduces price, advertising and distribution simultaneously, but it does not identify the specific effect of any dimension individually. His results show that the proposed model improves the original Bass model.

Over the last few decades, a fairly large body of research on international diffusion has appeared[3]. Researchers have addressed a number of issues such as the influence of country characteristics -*country effect*- (Gatignon, Eliashberg and Robertson, 1989; Takada and Jain, 1991; Helsen, Jedidi and DeSarbo, 1993; Dekimpe, Parker and Sarvary, 1998), the "waterfall" versus "sprinkler" strategies in the launch of new products across countries (Kalish, Mahajan and Muller, 1995), the time lag between introductions of new products among countries -*time effect*- (Helsen, Jedidi and DeSarbo, 1993; Takada and Jain, 1991; Mahajan and Muller, 1994; Kumar, Ganesh and Echambadi, 1998; Putsis et al., 1997; Elberse and Eliashberg, 2003), the pattern of cross-country interaction -or cross-country effect- (Mahajan and Muller, 1994; Eliashberg and Helsen, 1996; Putsis et al., 1997; Kumar and Krishnan, 2002).

[3] See also Chapter 2, Section 2.4.2.5.

Research on the *country effect* focuses on the influence that different environments (countries or specific geographical areas) have on the diffusion processes of innovations. The rationale behind this issue is that an innovation spreads in different ways among different cultures depending on the socio-cultural and socio-economic environments (Redmond, 1994; Dekimpe, Parker and Sarvary, 1998). Analyzing the introduction of a number of products into different countries, Gatignon, Eliashberg and Robertson (1989), Takada and Jain (1991), Helsen, Jedidi and DeSarbo (1993) and Dekimpe, Parker and Sarvary (1998) show that the differences in diffusion patterns could be attributed to country-specific factors such as geographical consumer mobility, cosmopolitanism, the role of women in the labor force, cultural level, prosperity, life-style, ethnic homogeneity, population growth rates or income/poverty levels.

Research on the *time effect* is concerned with how time lags, which necessarily occur when a new product is launched into different markets in a sequential order, affect the diffusion processes. In other words, when a new product is introduced in a country and some time later it is introduced in other countries, consumers in the lag countries learn about the product from the adopters in the lead country. This learning could lead to different diffusion patterns[4]. Putsis et al. (1997) point out that a sequential release provokes differences in information availability that lead to differences in diffusion patterns across markets. There is, however, no consensus among authors. No clear evidence exists on how the experience of adopters in the lead country affects the adoption decisions of potential adopters in the lag countries. Takada and Jain (1991), Mahajan and Muller (1994), and Kumar, Ganesh and Echambadi (1998), focusing on consumer durables, point out that the longer it takes to introduce an innovation into another country, the quicker the ultimate adoption process will be (a positive relationship between the diffusion parameters and the time lag). However, Helsen, Jedidi and DeSarbo (1993) demonstrate the opposite (a negative relationship). An innovation of a consumer durable that has been introduced in a pioneer country, produces a slowing effect on the diffusion processes in countries where the innovation is later introduced. With regard to the extent of the impact of time lags as opposed to their direction, Elberseand Eliashberg (2003), focusing on experience products, find that the longer the time lag between releases, the weaker the relationship between lead and lag countries. This implies that a movie's release in the following countries should be close to that of the pioneering country, given that this benefits the introduction of the innovation in the lag countries.

In this study we first consider three different diffusion models that all incorporate distribution. After selecting the most appropriate model to describe the diffusion processes of a group of movies in three different countries, we focus on analyzing the existence of *country* and *time effects*. The data covers three countries (Spain, France

[4] Ganesh and Kumar (1996) call this the learning effect.

and Italy), twenty-one movies are shown in Spain and six of these movies are also shown in France and Italy.

4.3. Modeling framework

We divide this section into two parts. In the first part we present and compare different diffusion models that explicitly incorporate the distribution variable, and in the second part we address a cross-national analysis by verifying whether the country specific characteristics and the moment of entrance influence the diffusion processes of innovations.

4.3.1. Diffusion models that include distribution

We calibrate three diffusion models and evaluate the goodness of fit with the correlation between the real and the estimated values of the dependent variables[5] (r), the sum of squared residuals (SSR) and the mean absolute percentage error (MAPE). We consider the Bass model as a naïve model. Two proposals are based on the work of Jain and Rao (1990), another is based on that of Bass, Krishnan and Jain (1994).

As we have seen in Section 2.3.2, the Bass model can be expressed as:

$$f(t) = [\beta_1 + \beta_2 F(t)][1 - F(t)] \tag{4.1}$$

where the random variable t denotes the moment of adoption of a new product by an individual (adopter), β_1 and β_2 are the parameters of innovation and imitation respectively, $f(t)$ is the probability of adoption at time t and $F(t)$ the cumulative distribution function:

$$F(t) = \frac{1 - e^{-(\beta_1+\beta_2)t}}{1 + \dfrac{\beta_1}{\beta_2} e^{-(\beta_1+\beta_2)t}}. \tag{4.2}$$

We will refer to the Bass model as model 1.

We specify two alternative models (models 2 and 3), which incorporate the distribution variable into the diffusion model. Both models are based on Jain and Rao (1990). The model considers dynamics in the potential number of adopters. If [$F(t)$-$F(t$-1)] is the probability that an (randomly chosen) individual adopts the new product within time interval (t-1, t), and if $\left[F(t) - F(t-1)\right] / \left[1 - F(t-1)\right]$ represents the

[5] We show r instead of R^2 or adjusted-R^2 since the proposed models do not have an intercept term (Judge et al., 1985, pp. 30-31).

conditional probability of an individual adopting within time interval (t-1, t) given that he has not yet adopted it at time t-1, we have:

$$S(t) = [M - N(t-1)]\left[\frac{F(t) - F(t-1)}{1 - F(t-1)}\right] + u(t) \quad (4.3)$$

where $S(t)$ represents sales over time interval (t-1, t), $N(t$-1) the total number of adopters by time t-1, and [M-$N(t$-1)] the potential market at time t.

The size of the potential market is directly influenced by the number of retailers who offer the new product[6]. We incorporate this number in model (4.3) in two ways:

In model 2, we assume that the number of retailers who offer the product (D) affects the potential market (M) in the following way:

(model 2)
$$S(t) = \left[M * D(t)^{\delta_1} - N(t-1)\right]\left[\frac{F(t) - F(t-1)}{1 - F(t-1)}\right] + v(t) \quad (4.4)$$

In model 3, we assume that the number of retailers who offer the product affects the effective potential market [M-$N(t$-1)][7]:

(model 3)
$$S(t) = \left[M - N(t-1)\right]D(t)^{\delta_2}\left[\frac{F(t) - F(t-1)}{1 - F(t-1)}\right] + w(t) \quad (4.5)$$

where δ_1 and δ_2 are the intermediation parameters, and $v(t)$ and $w(t)$ the error terms, with an average of 0 and variances of σ_v^2 and σ_w^2 respectively.

Finally, model 4 is derived from the Generalized Bass model -GBM- (Bass, Krishnan and Jain, 1994). The GBM is a model that incorporates the marketing variables of price and advertising. It has the following structure:

(model 4)
$$\frac{f(t)}{[1 - F(t)]} = \left[\beta_1 + \beta_2 F(t)\right]me(t) \quad (4.6)$$

where $me(t)$ reflects current and lagged marketing efforts. If price and advertising are considered at time t -$P(t)$ and $A(t)$, respectively-, $me(t)$ is a function of the percentages of change of such variables:

$$me(t) = 1 + \lambda_1 \frac{\Delta P(t)}{P(t-1)} + \lambda_2 \frac{\Delta A(t)}{A(t-1)} \quad (4.7)$$

where $\Delta P(t)$ and $\Delta A(t)$ are the changes in price and advertising at time t, respectively, and λ_1 and λ_2 are the diffusion price and advertising parameters,

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6 See Chapter 2, Section 2.4.2.2, for the authors that have relaxed this restriction and have proposed dynamic potential markets.

7 The term $D(t)^{\delta_2}$ has been included in Equation (4.5) in a multiplying way so that it will also affect the adoption rate $\frac{F(t) - F(t-1)}{1 - F(t-1)}$ (Jain and Rao, 1990).

respectively; they control the effect of price and advertising, respectively, in accelerating and desaccelerating the diffusion process.

For our particular case, where the marketing variable considered is distribution (in terms of the number of retailers of the new product, *D*), we use:

$$me(t) = 1 + \delta_3 \frac{\Delta D(t)}{[D(t-1)]} \tag{4.8}$$

where parameter δ_3 is the intermediation parameter. Its expected value is positive, since an increase in the number of retailers favors the diffusion process.

The idea behind the proposed models (models 2, 3 and 4) is that the diffusion process of an innovation is governed by the innate innovativeness of consumers and mass media communication, social contagion and also by the number of retailers offering the innovation.

4.3.2. Country and time effects

We now examine the possible differences that may exist in the diffusion parameters of geographically close European countries and the effect that the moment of the innovation's introduction may have on the speed of its adoption in these different countries. The geographical comparisons are made in terms of the parameter of internal influence (parameter of imitation in the Bass model), since (1) the number of imitators of an innovation is generally much greater than the number of innovators, and (2) the imitators are the ones who, through social interaction, influence the diffusion process most (Takada and Jain, 1991; Redmond, 1994).

Previous research (Gatignon, Eliashberg and Robertson, 1989; Takada and Jain, 1991; Helsen, Jedidi and DeSarbo, 1993; Dekimpe, Parker and Sarvary, 1998) on the introduction of innovations into different countries shows that the differences in diffusion patterns could be attributed to country-specific factors such as geographical consumer mobility, cosmopolitanism, the role of women in the labor force, cultural level, prosperity, life-style, ethnic homogeneity, population growth rates or income/poverty levels. Since there are specific country factors that can influence consumer behavior regarding innovations, we test for differences in the diffusion processes of the geographical areas analyzed, i.e. whether there is a *country effect*. Hence, hypothesis 1 is expressed as:

H_1: *The parameter of internal influence, β_2, varies among countries*

We test hypothesis 1 by using an analysis of variance test for all of the countries considered and statistical tests for differences between pairs of countries.

We consider the time lag between the moment an innovation is introduced into the pioneering country (or lead country) and the moment it is introduced into a following country (or a lag country). This time lag can affect the diffusion pattern in the following country. No clear evidence exists on how the experience of adopters in the lead country affects the adoption decisions of potential adopters in the lag countries. Some researchers, such as Takada and Jain (1991), Mahajan and Muller (1994), and Kumar, Ganesh and Echambadi (1998) find that the longer it takes to introduce an innovation into another country, the quicker the ultimate adoption process will be. However others, such Helsen, Jedidi and DeSarbo (1993), find the opposite (see Section 4.2). Accordingly, we test whether time lags affect the diffusion processes in the different geographical areas we are analyzing, i.e. whether there is a *time effect*. Hence, hypothesis 2 is expressed as:

H_2: *The time lag between introductions in two different countries affects the adoption process in the last country in which the product is introduced.*

We test hypothesis 2 with the model proposed by Takada and Jain (1991):

$$y_{ijk} = \alpha_0 + \alpha_1 x_{ijk} + \mu_{ijk} \tag{4.9}$$

where y_{ijk} and x_{ijk} are the differences in the values of the imitation parameters and introduction years for a pair of countries *i* and *j* for product *k*, respectively, α_0 and α_1 are parameters and μ_{ijk} is the error term. We test whether α_1 is significantly different to zero. As in the *country effect*, we test hypothesis 2 across the three countries and between pairs of countries.

4.4. Sample, data and measurement of the variables

Movies are consumer products that can be characterized as entertainment and experience products. It is difficult for consumers to evaluate the quality of movies until after their adoption (Neelameghan and Jain, 1999; Elberse and Eliashberg, 2003). Consumers rely heavily on comments from the people closest to them (family, friends and work-mates) on the movies that are currently being shown, (internal influence), and the promotion that movies receive in the mass media (external influence). Accordingly, movies are appealing products for this research since *a priori* the use of diffusion models of innovations[8] of mixed influence seems appropriate.

Our study focuses on three European Mediterranean countries -Spain, France and Italy-, between September 1997 and March 1999. We examine a total of twenty-one new movies launched in Spain, eight of them also in France, and nine also in Italy (see

[8] Motion picture marketers believe that every motion picture (movie) is unique (Eliashberg et al., 2000), hence each movie has to be considered as a new product

Table 4.1). We only select movies that were exhibited for at least six weeks[9]. The length and form of the product life of the movies differ from one country to another[10].

Table 4.1. Movies analyzed by country.

		SPAIN		FRANCE		ITALY	
Code	Title	Weeks[1]	Launch	Weeks	Launch	Weeks	Launch
1	*The Girl of Your Dreams*	15	15/11/98	-	-	-	-
2	*The Mask of Zorro*	10	29/11/98	7	20/10/98	-	-
3	*P. Tinto's Miracle*	7	20/12/98	-	-	-	-
4	*Mulan*	7	22/11/98	7	01/12/98	-	-
5	*There's Something About Mary*	10	08/11/98	9	17/11/98	8	22/09/98
6	*Saving Private Ryan*	8	20/09/98	8	06/10/98	7	05/11/98
7	*Six Days, Seven Nigths*	8	16/08/98	-	-	-	-
8	*Argameddon*	8	19/07/98	9	11/08/98	-	-
9	*Deep Impact*	7	17/05/98	6	02/06/98	11	21/05/98
10	*The Big Lewoski*	7	17/05/98	-	-	13	07/05/98
11	*Torrente el Brazo Tonto de la Ley*	15	15/03/98	-	-	10	23/07/98
12	*As Good as It Gets*	7	01/03/98	-	-	-	-
13	*The Man in the Iron Mask*	9	12/04/98	6	07/04/98	7	02/04/98
14	*The Full Monty*	19	12/09/97	13	28/10/97	10	19/03/98
15	*Open Your Eyes*	8	21/12/97	-	-	-	-
16	*Seven Years in Tibet*	7	07/12/97	9	02/12/97	-	-
17	*Hercules*	7	23/11/97	-	-	-	-
18	*The Truman Show*	7	01/11/98	-	-	6	12/11/98
19	*Blade*	7	11/09/98	-	-	-	-
20	*The Horse Whisperer*	7	04/09/98	10	08/09/98	6	22/11/98
21	*The Jackal*	7	25/01/98	-	-	-	-

(1): Length of the life cycle of the movie in weeks.
(-): Insufficient information or none available.
SOURCE: *Variety Magazine* (1997, 1998, 1999)

The distribution variable (or the exhibition intensity) is defined as the number of retailers or exhibitors (using the terminology of the motion picture industry) that exhibit the movies examined. We obtain information from *Variety Magazine*, a leading American trade publication of the motion picture industry that provides weekly data on the number of screens where a movie is being exhibited and the box-

[9] Jones and Ritz (1991) discard movies that run for under five weeks.
[10] The life cycle of a typical movie is less than fifteen weeks in the domestic theatrical release (Sawhney and Eliashberg, 1996).

office revenues per screen, according to geographical areas. Finally, the number of spectators has been computed, based on the weekly box-office revenues for each movie, as well as the average price of an entrance ticket, obtained through the Institute of Cinema and Audiovisual Arts (ICAA) in Spain and from the different Embassies.

We focus the study on Spain, France and Italy for several reasons. Firstly, although *Variety Magazine* provides information for ten countries each week, it does not always show the same countries, which means that, for some countries, it is not possible to collect data for a movie exhibited over at least six weeks. Secondly, we are interested in European countries since there is little research on non-US markets. Thirdly, the average price of an entrance ticket was unobtainable for some countries.

4.5. Empirical results

In this section, we first discuss the results we obtain from the model estimation. Next, we test the hypotheses that have been specified in Section 4.3.2 on differences in diffusion patterns among the three Mediterranean countries.

4.5.1. Diffusion model performance

We apply the proposed mixed influence diffusion models to Spanish data. We need non-linear estimation procedures (NLS) (Jain and Rao, 1990) to obtain parameter estimates[11]. For model comparison, we use the fit statistics (MAPE, SSR and r), parameter face validity and the Akaike Information Criterion. However, we have to take into account that since prediction is not the aim of this study, parameter face validity is crucial for evaluating alternative marketing decisions and also to develop the analyses in Section 4.5.2. The parameter estimates and the goodness-of-fit statistics for each movie are shown in Appendix 4A (Table 4A.1).

Examining the estimates, we see that the estimates of external influence, $\hat{\beta}_1$, is significant in 95%, 84%, 42% and 94% of the movies examined by models 1, 2, 3 and 4 respectively, while the estimates of internal influence, $\hat{\beta}_2$, is significant in 66%, 63%, 50% and 73% of the movies analyzed by models 1, 2, 3 and 4 respectively. The estimates of β_1 and β_2 exhibit face validity in terms of their magnitude[12] and direction

[11] Srinivasan and Mason (1986) were the first authors to propose an NLS approach to estimate the parameters in the Bass model.

[12] In their meta-analysis of 213 applications of diffusion models from 15 articles, Sultan, Farley and Lehmann (1990) find that word-of-mouth shows bigger magnitudes than the parameter of external influence.

(see Table 4.2). These results confirm that the consumer adoption process for movies is very sensitive to internal communication (as pointed out by Eliashberg, Jonker, Sawhney and Wierenga (2000)) but also to external communication. In other words, when the Spanish public has to choose one of the movies analyzed in the sample, they are influenced by both sources, the comments of people in their face-to-face group and the promotion of the movies.

The intermediation parameter estimates, $\hat{\delta}_1$, $\hat{\delta}_2$ or $\hat{\delta}_3$, are significant in more than 15%, 50% and 15% of the movies analyzed by models 2, 3 and 4 respectively (see Table 4.2). The significant estimates show the right signs, indicating that the diffusion process of these movies is enhanced by an increase in the number of screens, albeit to a small extent, as the negative signs in models 2 and 3 reveal.

Table 4.2.
Plausibility of estimates - $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\delta}_1$, $\hat{\delta}_2$, $\hat{\delta}_3$ - (Spanish data)

	Relative frequencies(1)							
	Model 1		Model 2		Model 3		Model 4	
	Level	%	Level	%	Level	%	Level	%
External influence parameter -β_1-								
Right sign and expected magnitude								
Significant estimates	20/21	95	16/19	84	6/14	43	18/19	95
Non-significant estimates	1/21	5	4/19	21	8/14	57	1/19	5
Wrong sign and non-expected magnitude	0/21	0	0/19	0	0/14	0	0/19	0
Internal influence parameter -β_2-								
Right sign and expected magnitude								
Significant estimates	14/21	67	12/19	63	7/14	50	14/19	74
Non-significant estimates	7/21	33	7/19	37	7/14	50	5/19	26
Wrong sign and non-expected magnitude	0/21	0	0/19	0	0/14	0	0/19	0
Intermediation parameter								
-δ_1-								
Significant estimates			3/19	16				
Non-significant estimates			16/19	84				
-δ_2-								
Significant estimates					7/14	50		
Non-significant estimates					7/14	50		
-δ_3-								
Right sign								
Significant estimates							3/19	16
Non-significant estimates							13/19	68
Wrong sign								
Significant estimates							0/19	0
Non-significant estimates							3/19	16

(1): The number of movies differs among models due to convergence problems.

We analyze the benefit of adding one more parameter to the Bass model. In this respect we follow Bemmaor and Lee (2002). On average, the improvement in MAPE for models 2, 3 and 4 is 17%, 41% and 12% over the corresponding Bass model (see Table 4.3). Therefore, adding the intermediate parameter to the Bass model improves the descriptive accuracy of the model.

Table 4.3.
Benefit of the intermediation parameter (Spanish data)

	Model 1	Model 2	Model 3	Model 4
Avg. MAPE (%)	15,45	12,88	9,15	13,60
Improvement[(1)] (%)		17	41	12

(1): $\text{Improvement}_i = \left(1 - \dfrac{\text{Avg. MAPE}_i}{\text{Avg. MAPE}_1}\right) * 100$, $i = 2,3,4$; where sub-index i is referred to model.

The inclusion of the distribution variable in the models allows us to understand how distribution can affect the diffusion process of a movie. This corresponds to the findings of Jones and Ritz (1991) and Neelameghan and Chintagunta (1999). Jones and Ritz (1991) present evidence that retailers' adoption of screens is a key determinant of movie viewership in the United States. Neelameghan and Chintagunta (1999) find that the number of screens on which a movie is released is the most important influence on viewership among the factors that they analyzed (movie attributes such as genre or presence/absence of stars).
The level of significant estimates ($\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\delta}_1$, $\hat{\delta}_2$ or $\hat{\delta}_3$, depending on the model) with right signs in model 2, 3 and 4 are at 54%, 48% and 61%, respectively (see Table 4.3). In general terms, model 4 shows better results than models 2 and 3.

Table 4.3.
Plausibility of estimates - $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\delta}_1$, $\hat{\delta}_2$, $\hat{\delta}_3$ - in general terms (Spanish data)

	Relative frequencies[(1)]					
	Model 2		Model 3		Model 4	
	($\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\delta}_1$)		($\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\delta}_2$)		($\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\delta}_3$)	
	Level	%	Level	%	Level	%
Significant estimates	31/57	54	20/42	48	35/57	61

(1): The number of movies differs among models due to convergence problems.

Looking at the fitting results (r, SSR and MAPE), Table 4A.1 (see Appendix 4A) shows that the proposed models describe the adoption of movies quite well. The correlation level, r, is higher than 0.90 in more than 83% of the cases (61 out of 73). Identical results are obtained when we examine SSR and MAPE. No model, however, shows a clearly better fit than the others for all the movies examined. However, the Akaike Information Criterion shows that, among models 2, 3 and 4, model 3 is the preferred model in 48% (10 out of 21) of the cases (Table 4.4).

Table 4.4.
Akaike Information Criterion -AIC- (Spanish data)

Movie (code)	Model	AIC	Movie (code)	Model	AIC	Movie (code)	Model	AIC	Movie (code)	Model	AIC
1	Mod.2	23.86	7	Mod.2	24.68	13	Mod.2	24.95	19	Mod.2	25.01
	Mod.3	23.84		*Mod.3*	*23.49*		*Mod.3*	*24.26*		Mod.3	-
	Mod.4	*23.75*		Mod.4	25.43		Mod.4	25.16		Mod.4	-
2	Mod.2	25.02	8	Mod.2	24.84	14	Mod.2	23.94	20	Mod.2	22.34
	Mod.3	25.01		*Mod.3*	*22.29*		*Mod.3*	*23.54*		*Mod.3*	*21.00*
	Mod.4	*24.97*		Mod.4	24.80		Mod.4	23.87		Mod.4	23.14
3	Mod.2	22.24	9	*Mod.2*	*23.86*	15	Mod.2	25.18	21	*Mod.2*	*23.75*
	Mod.3	-		Mod.3	-		*Mod.3*	*21.03*		Mod.3	-
	Mod.4	-		Mod.4	24.42		Mod.4	23.79		Mod.4	24.58
4	Mod.2	25.64	10	Mod.2	-	16	*Mod.2*	*25.44*			
	Mod.3	25.51		*Mod.3*	*19.24*		Mod.3	-			
	Mod.4	*25.50*		Mod.4	21.27		Mod.4	25.52			
5	Mod.2	25.21	11	Mod.2	24.31	17	*Mod.2*	*25.79*			
	Mod.3	*25.16*		*Mod.3*	*24.16*		Mod.3	25.59			
	Mod.4	25.29		Mod.4	24.53		Mod.4	25.73			
6	Mod.2	25.35	12	Mod.2	-	18	*Mod.2*	*23.80*			
	Mod.3	*23.73*		Mod.3	-		Mod.3	-			
	Mod.4	25.60		Mod.4	24.28		Mod.4	24.69			

Cursive indicates the smallest AIC.

In order to compare the results across countries, the four proposed models are applied to the six movies that were shown in all three countries -Spain, France and Italy- (see Appendix 4A, Table 4A.2).

Examining Table 4A.2 (see Appendix 4A) we see that for the French data, the estimate of β_1 is significant in 4, 3, 0 and 4 of the movies examined by models 1, 2, 3 and 4 respectively. The estimate of β_2 is significant in 2, 0, 0 and 3 for models 1 through 4, respectively[13]. For the Italian data, the estimate of β_1 is significant in 6, 6, 1 and 6 for models 1 through 4 while the estimate of β_2 is significant in 6, 4, 2 and 5 for models 1 through 4, respectively[14] (see Table 4.5)

Table 4.5.
Plausibility of estimates - $\hat{\beta}_1$, $\hat{\beta}_2$ - (Spanish, French and Italian data)

	Relative frequencies[(1)]							
	Model 1		Model 2		Model 3		Model 4	
	Level	%	Level	%	Level	%	Level	%
External influence parameter -β_1-								
Spanish data								
Right sign and expected magnitude								
Significant estimates	6/6	100	6/6	100	2/5	40	6/6	100
Non-significant estimates	0/6	0	0/6	0	3/5	60	0/6	0
French data								
Right sign and expected magnitude								
Significant estimates	4/6	67	3/3	100	0/3	100	4/6	67
Non-significant estimates	2/6	33	0/3	0	3/3	0	2/6	33
Italian data								
Right sign and expected magnitude								
Significant estimates	6/6	100	6/6	100	1/2	50	6/6	100
Non-significant estimates	0/6	0	0/6	0	1/2	50	0/6	0
Internal influence parameter -β_2-								
Spanish data								
Right sign and expected magnitude								
Significant estimates	6/6	100	5/6	83	2/5	40	5/6	83
Non-significant estimates	0/6	0	1/6	17	3/5	60	1/6	17
French data								
Right sign and expected magnitude[(2)]								
Significant estimates	2/6	33	0/3	100	0/3	100	3/6	50
Non-significant estimates	2/6	33	3/3	0	3/3	0	1/6	17
Italian data								
Right sign and expected magnitude								
Significant estimates	6/6	100	4/6	67	2/2	100	5/6	83
Non-significant estimates	0/6	0	2/6	33	0/2	0	1/6	17

(1): The number of movies differs among models due to convergence problems.
(2): 2 out of 6 estimates for β_2 in model 1 and also 2 in model 4 show wrong signs although these are not significant. These four are the only cases with wrong sign estimates.

[13] For the French data, the estimation approach of models 2 and 3 converges in three out of the six movies.
[14] For the Italian data, the estimation approach of model 3 converges in two out of the six movies.

Hence, in the three European countries, the estimates of β_1 and β_2 exhibit face validity in terms of magnitude and direction, and the level of significance of these estimates exceeds 66% (4 out of 6 movies) in all of the models, except for model 3 and for $\hat{\beta}_2$ for the French data. These results confirm the importance of external and internal communication in the diffusion of this group of movies in the three countries and support the movie industry specialists when they emphasize the importance of intangible factors such as consumer perceptions (external influence) and word-of-mouth (internal influence) to forecast movie success (Neelameghan and Jain, 1999).

Concerning the intermediation parameter -δ_1, δ_2 or δ_3, depending on the model-, the results show that across the three countries (in Spain, France and Italy) the estimates are significant in 2 out of 15, 4 out of 10 and 6 out of 18 of the movies analyzed by models 2, 3 and 4 respectively (see Table 4.6).

Table 4.6.
Plausibility of estimates - $\hat{\delta}_1$, $\hat{\delta}_2$, $\hat{\delta}_3$ - (Spanish, French and Italian data)

	Relative frequencies[1]					
	Model 2		Model 3		Model 4	
Intermediation parameters	Level	%	Level	%	Level	%
-δ_1-						
Spanish data						
Significant estimates	1/6	17				
Non-significant estimates	5/6	83				
French data						
Significant estimates	0/3	0				
Non-significant estimates	3/3	100				
Italian data						
Significant estimates	1/6	17				
Non-significant estimates	5/6	83				
-δ_2-						
Spanish data						
Significant estimates			4/5	80		
Non-significant estimates			1/5	20		
French data						
Significant estimates			1/3	33		
Non-significant estimates			2/3	67		
Italian data						
Significant estimates			2/2	100		
Non-significant estimates			0/2	0		
-δ_3-						
Spanish data						
Right sign						
Significant estimates					1/6	17
Non-significant estimates					4/6	67
Wrong sign						
Significant estimates					0/6	0
Non-significant estimates					1/6	17
French data						
Right sign						
Significant estimates					1/6	17
Non-significant estimates					2/6	33
Wrong sign						
Significant estimates					0/6	0
Non-significant estimates					3/6	50
Italian data						
Right sign						
Significant estimates					4/6	67
Non-significant estimates					2/6	17
Wrong sign						
Significant estimates					0/6	0
Non-significant estimates					0/6	0

(1): The number of movies differs among models due to convergence problems.

Across the three countries, on average, the improvement in MAPE for models 2, 3 and 4 is 32%, 37% and 18% over the corresponding Bass model in the three countries (see Table 4.7). Therefore, adding the intermediate parameter to the Bass model improves the descriptive accuracy of the model. Again, despite the small number of significant estimates of the intermediation parameter, the estimates indicate that the diffusion process of these movies is enhanced by an increase in the number of screens.

Table 4.7.
Benefit of the intermediation parameter (Spanish, French and Italian data)

	Model 1	Model 2	Model 3	Model 4
Spanish data				
Avg. MAPE[(1)] (%)	17,65	11,67	11,35	14,75
Improvement[(2)] (%)		34	36	16
French data				
Avg. MAPE (%)	18,75	7,91	13,22	17,98
Improvement (%)		58	29	4
Italian data				
Avg. MAPE (%)	19,74	16,01	10,98	13,25
Improvement (%)		19	44	33
All countries				
Avg. MAPE (%)	18,71	12,65	11,83	15,33
Improvement (%)		32	37	18

(1): $\text{Avg. MAPE}_\text{i} = \dfrac{\sum_{j=1}^{6}\sum_{i=1}^{4}\text{MAPE}_{ij}}{M_i}$, $i = 1,2,3,4$, $j = 1,2,\ldots 6$; where sub-index i is referred to model, j to movie and M_i to the number of movies where the estimation approach converges for model i.

(2): $\text{Improvement}_i = \left(1 - \dfrac{\text{Avg. MAPE}_i}{\text{Avg. MAPE}_1}\right) * 100$, $i = 2,3,4$; where sub-index i is referred to model.

We see that the level of significant estimates ($\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\delta}_1$, $\hat{\delta}_2$ or $\hat{\delta}_3$, depending on the model) with right signs in model 2, 3 and 4 are at 58%, 40% and 65%, respectively (see Table 4.8). This indicates that, across the three countries, model 4 shows better results (in terms of face validity) than models 2 and 3; as with the Spanish data.

Table 4.8.
Plausibility of estimates - $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\delta}_1$, $\hat{\delta}_2$, $\hat{\delta}_3$ - across the three countries (Spanish, French and Italian data)

	Relative frequencies[1]					
	Model 2		Model 3		Model 4	
	($\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\delta}_1$)[2]		($\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\delta}_2$)[2]		($\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\delta}_3$)[2]	
	Level	%	Level	%	Level	%
Spain	12/18	66.67	8/15	53.33	12/18	66.67
France	3/9	33.33	1/9	11.11	8/18	44.44
Italy	11/18	61.11	3/6	50.00	15/18	83.33
All countries	26/45	57.78	12/30	40.00	35/54	64.81

(1): The number of movies differs among models due to convergence problems.
(2): Significant estimates

Looking at the fitting results (r, SSR and MAPE), they indicate that, as with the Spanish data, the proposed models describe the adoption of movies quite well with the French and Italian data (see Appendix 4A, Table 4A.2). The correlation level, r, is higher than 0.90 in more than 88% of the cases (16 out of 18) and in 100% (20 out of 20) of the cases, respectively. Identical results are obtained when we examine SSR and MAPE. Once again, no model, however, shows a clearly better fit than the others for all the movies examined. However, the Akaike Information Criterion shows that, across the three countries, among models 2, 3 and 4, model 4 is the preferred model in 61% of the cases (11 out of 18) (Table 4.9).

Table 4.9.
Akaike Information Criterion -AIC-
(Spanish, French and Italian data)

Movie (code)	Spain Model	Spain AIC	France Model	France AIC	Italy Model	Italy AIC
5	Mod.2	25.21	Mod.2	-	Mod.2	22.30
	Mod.3	*25.16*	Mod.3	-	Mod.3	22.14
	Mod.4	25.29	Mod.4	24.70	*Mod.4*	*21.15*
6	Mod.2	25.35	*Mod.2*	*23.37*	Mod.2	23.07
	Mod.3	*23.73*	Mod.3	-	Mod.3	-
	Mod.4	25.60	Mod.4	23.48	*Mod.4*	*23.05*
9	*Mod.2*	*23.86*	Mod.2	-	Mod.2	20.95
	Mod.3	-	Mod.3	-	Mod.3	-
	Mod.4	24.42	Mod.4	26.43	*Mod.4*	*20.50*
13	Mod.2	24.95	Mod.2	24.34	Mod.2	25.20
	Mod.3	*24.26*	Mod.3	24.23	Mod.3	-
	Mod.4	25.15	*Mod.4*	*24.08*	*Mod.4*	*24.97*
14	Mod.2	23.94	Mod.2	-	Mod.2	24.13
	Mod.3	*23.54*	Mod.3	23.74	Mod.3	23.72
	Mod.4	23.87	*Mod.4*	*23.54*	*Mod.4*	*23.16*
20	Mod.2	22.34	Mod.2	23.46	Mod.2	22.00
	Mod.3	*21.00*	Mod.3	23.37	Mod.3	-
	Mod.4	23.14	*Mod.4*	*23.23*	*Mod.4*	*19.09*

Cursive indicates the smallest AIC.

The face validity and fitting results for the proposed models show that in general terms models 1, 2, 3 and 4 are adequate in terms of explaining the diffusion process of movies. However, comparing the results for those models that take into account the intermediate parameter, model 4 shows better results. In terms of the number of significant estimates, model 4 shows, across the three countries, the highest percentage and when we combine the indicators of goodness of fit, model 4 gives the greatest r (12 out of 18, 67%) and the smallest SSR (11 out of 18, 61%) and MAPE values (7 out of 18, 39%) in more cases than the other models. Furthermore, the Akaike Information Criterion reveals that among models 2, 3 and 4, model 4 is the preferred model. Hence, the results indicate that model 4 is the most appropriate diffusion model to describe the diffusion process of the selected movies in the three Mediterranean countries, taking distribution into account.

In summary, the results for model 4 in Spain, France and Italy show that the estimates of the parameter of external influence, $\hat{\beta}_1$, are significant for 16 out of 18 movies analyzed (89%), and those of internal influence, $\hat{\beta}_2$, are significant for 13 movies (72%). The estimate the intermediation parameter, $\hat{\delta}_3$, which measures the effectiveness of distribution, is only significant for 6 out of 18 movies (33%). The positive values of $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\delta}_3$ are as expected, since the diffusion process of these movies was enhanced by longer exposure to inter-personal and mass communication, and by an increase in the number of screens. Despite the findings showing the influence of the intermediation parameter on the diffusion processes, we have only enough statistical evidence to state that the parameters of external and internal influence clearly govern the diffusion patterns of the examined movies in the analyzed countries.

4.5.2. Differences among diffusion processes

We analyze whether significant differences exist among the diffusion processes of the six movies shown in Spain, France and Italy. We also study the effect that the time lag in the moment of introduction of the movies regarding the pioneering (lead) country has on the diffusion processes of the following (lag) countries. Given the results obtained in the previous stage, the Generalized Bass model (GBM) extended to distribution -model 4- is used for the cross-national analysis of diffusion processes of movies in the three European countries.

The country effect

Hypothesis 1 -*The parameter of internal influence, β_2, varies among countries*- is tested by using two different tests, a global one to find differences in the diffusion processes for the three countries simultaneously and separate ones for each pair of countries. Given the estimates of the parameter of internal influence, $\hat{\beta}_2$, we are now able to test whether internal influence differs between countries. To this we apply a test that considers all $\hat{\beta}_2$'s simultaneously. The analysis of variance[15] (F-statistic = 13.97, d.f. = (2, 15), prob. = 0.0004) reveals that Hypothesis 1 is confirmed with a confidence level of 99%.

[15] Although we use the estimates of the parameter of internal influence, $\hat{\beta}_2$ (model 4, Table 4.4), the same analysis (F-statistic = 1.02, d.f. = (2, 15), prob. = 0.3850) using the estimates of the parameter of external influence, $\hat{\beta}_1$ (model 4, Table 4.4), reveals similar $\hat{\beta}_1$*'s* among Spain, France and Italy.

There is a *country effect* in the diffusion processes. In other words, the three countries show sufficient differences to yield different consumer behavior patterns and, hence, different diffusion processes for the group of analyzed movies.

We also study whether the differences in the estimates of the parameter of internal influence, $\hat{\beta}_2$, are significant when the countries are examined in pairs. These differences (see Table 4.10) are significant between the pairs of Spain-France and France-Italy, with a confidence level of 95% and 99%, respectively. The differences are not significant, however, in the case of Spain-Italy[16]. Hence, the tests do not detect any important cultural, economic and/or social differences between these two Mediterranean countries that could have caused different preferences for the group of movies analyzed. On the other hand, the geographical closeness of France and her two European neighbors (Spain and Italy) is not sufficient to eliminate the differences in their intrinsic characteristics. The results clearly indicate that a *country effect* does exist between France and Spain, and between France and Italy.

Table 4.10.
Tests for equality of means among countries (t-test).

$\hat{\beta}2(France)$ - $\hat{\beta}2(Spain)$	$\hat{\beta}2(Spain)$ - $\hat{\beta}2(Italy)$	$\hat{\beta}2(France)$ - $\hat{\beta}2(Italy)$
3.56**	0.73	4.86***

***: $p \leq 0.001$; **: $p \leq 0.05$

To the question proposed by Takada and Jain (1991, p.48), "*Are there any cross-national differences in diffusion processes between the home country and the foreign market where the product is to be introduced?*", our results reveal that the geographic, socio-economic, demographic and/or cultural characteristics or other aspects of the Spanish and Italian markets are not different enough to show relevant differences in the diffusion processes of the analyzed group of movies. These characteristics are sufficiently different between these countries and France.

The time effect

In studying the *time effect* it is necessary to observe a sequential release strategy. Table 4.1 reveals that the movies are released in Spain, France and Italy in

[16] We carried out this analysis considering the significant and non-significant estimates of β_2, and we repeat the same analysis by changing the not significant estimates to zeros. The results do not change.

a sequential order[17]. Spain is the pioneering country for three of the six movies (*Saving private Ryan, Deep impact* and *The horse whisperer*) and Italy in the other three (*There's something about Mary, The man in the iron mask* and *The full Monty*). Although there is not a single pioneering country for all the movies, France is revealed as a lag country.

Hypothesis 2 -*The time lag between introductions in two different countries affects the adoption process in the last country in which the product is introduced*- is tested by using the regression model specified in Equation (4.9). The parameter α_1 allows us to verify whether the time lag in the introduction of a new movie either speeds up or slows down the diffusion process in the lag countries.

We estimate α_1 by using Ordinary Least Squares. The results ($\hat{\alpha}_1 = 0.02$, prob. = 0.13), which show that $\hat{\alpha}_1$ is not significantly different from zero[18], indicate that there is insufficient empirical evidence for the hypothesis that a time lag in the introduction of new movies into the examined countries affects the diffusion processes, especially, the imitating behavior of adopters. One possible reason for this result is that as the differences in time between the moments of entrance of the movies in each country is very small, it is not easy to detect any effect on the parameter of internal influence.

Examining Table 4.11 we see the same results as those obtained across the three countries. The *time effect* between pairs of countries is not supported by the data.

Table 4.11.
Time effect between pairs of countries.

	$\hat{\alpha}_1$
(Spain, France)	-0.02
(Spain, Italy)	0.01
(France, Italy)	0.03

None of the estimates is significant

[17] There is one exception since *The man in the iron mask* was released in Spain and France on different days but within the same week.
[18] We carried out this analysis considering the significant and not significant estimates of β_2, and we repeat the same analysis by changing the not significant estimates to zeros. The results do not change. Since, the previous change makes the dependent variable take a value equal to zero sometimes and given that Least Squares applied to a truncated sample can provide biased and inconsistent estimates of the unknown parameters (Judge et al., 1985), we repeat the analysis using Maximum Likelihood instead of Ordinary Least Squares, but the results do not change.

Whereas the *country effect* is one of the reasons for the differences in the diffusion processes of movies in two of the three analyzed countries, the *time effect* does not appear to play a role.

4.6. Conclusions

This research focuses on two of the multiple concerns that managers have regarding the diffusion process of innovations: marketing decision variables and introductions into different markets. Although research on price and advertising is extensive in diffusion modeling, research on distribution is an area that should be addressed more extensively.

Researchers believe that both the socio-economic environment and time lags in introducing the new products into a market are relevant factors in explaining differences among diffusion processes of the same product in different geographical areas. These questions have motivated us to analyze these phenomena in the context of movies, in three Mediterranean European countries, between 1997 and 1999.

Distribution is incorporated into the diffusion models following the proposals of Jain and Rao (1990), who consider price, and those of Bass, Krishnan and Jain (1994), who consider price and advertising. Then we examine whether there are differences among the diffusion patterns of different countries -*country effect*-, as well as how time lags in the introduction of a group of movies into different countries may affect the diffusion processes -*time effect*-.

The empirical application carried out in the three Mediterranean European countries shows that the diffusion process of the analyzed group of movies is appropriately described by the proposed model. However, in the Spanish context the fitting results point out model 3 and the face validity model 4 as the best models. Nevertheless, across the three countries (Spain, France and Italy), results reveal model 4 as the preferred model. Model 4, derived from the Generalized Bass model (GBM) is a flexible model, easy to implement, which nests the Bass model as a special case and incorporates distribution as a marketing decision variable. In model 4, it is obvious that the influence of external sources and the experience of previous adopters are basic factors in reducing the uncertainty of new adopters regarding new movies. The simple knowledge of the existence of an innovation is not enough for an individual to become a new adopter, social communication is a key factor. Accordingly the diffusion processes of the analyzed movies are determined by three factors: two clear factors are the internal knowledge that consumers have about the movies (through advertising, critic reviews or their innate innovativeness) and word-of-mouth interactions (through social contagion among friends, colleagues or other close people who have already seen the movie), another possible factor is the intensity distribution of the movie in the country concerned.

We have detected a *country effect*, i.e. significant differences in consumer preferences between Spain and France and between Italy and France, although not between Spain and Italy. The slight cultural, economic or social differences that might exist between Spain and Italy do not seem to be large enough to provoke any significant difference between the internal influence parameters of their diffusion processes. Despite the idiosyncrasy in Spain and Italy, consumer behavior seems to be more similar than different, and this fact is reflected in the diffusion patterns.

In this sense, the findings of this study reinforce existing knowledge in the area by supporting the theses of Gatignon, Eliashberg and Robertson (1989), Takada and Jain (1991), Helsen, Jedidi and DeSarbo (1993), Redmond (1994) and Kumar, Ganesh and Echambadi (1998), which point out the importance of the own country characteristics in the commercialization of innovations. The knowledge that there are significant similarities between two countries, in our case Spain and Italy, allows managers to design similar marketing plans when they are thinking of commercializing the same innovation in both countries.

Finally, the results do not support the existence of a *time effect* among the analyzed countries. We do not find enough empirical evidence to obtain any conclusions on the hypothesis that time lags in the launch of movies in different countries either accelerate or decelerate the diffusion processes.

Appendix 4A. Summary tables

Table 4A.1.
Parameter estimates for Spain

Movie (code)	Weeks	Model	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{M}$ (10^3)	$\hat{\delta}_1$, $\hat{\delta}_2$ or $\hat{\delta}_3$	r	SSR (10^6)	MAPE
1	15	Mod.1	0.09 ***	0.09	2,854 ***		0.91	11,900	15.77
		Mod.2	0.09 ***	0.09	2,573	0.02	0.91	11,900	16.42
		Mod.3	0.01	0.07	2,829 ***	0.44	0.92	11,700	15.39
		Mod.4	0.09 ***	0.09 *	2,902 **	0.74	0.99	10,600	17.26
2	10	Mod.1	0.13 ***	0.42 ***	4,325 ***		0.99	19,600	8.56
		Mod.2	0.13 ***	0.44 **	4,767 **	-0.02	0.99	19,300	6.37
		Mod.3	0.16 **	0.48 **	4,353 ***	-0.04	0.99	19,200	6.76
		Mod.4	0.13 ***	0.41 ***	4,396 ***	1.35	0.99	18,400	7.44
3	7	Mod.1	0.24 **	0.25	1,082 ***		0.97	2,350	14.80
		Mod.2	0.23 **	0.61 **	8,176	0.61 **	0.99	596	7.91
		Mod.3	Do not converge						
		Mod.4	Do not converge						
4	7	Mod.1	0.10 **	0.30	3,026 **		0.72	18,200	14.17
		Mod.2	0.09	0.29	23,068	-0.36	0.73	17,900	14.83
		Mod.3	0.02	0.25	2,538	0.40	0.77	15,560	12.10
		Mod.4	0.09 **	0.35	2,985 **	-1.23	0.74	15,600	12.75
5	10	Mod.1	0.11 ***	0.24	3,818 ***		0.92	29,000	15.82
		Mod.2	0.09 **	0.15	1,153	0.26	0.93	22,200	10.10
		Mod.3	0.0002	0.11	4,435	1.17	0.94	22,000	10.06
		Mod.4	0.10 ***	0.20 *	4,153 ***	0.84	0.96	25,400	11.06
6	8	Mod.1	0.15 ***	0.51 **	2,632 ***		0.96	22,800	13.11
		Mod.2	0.14 **	0.68 **	9,265	-0.25	0.97	17,600	10.61
		Mod.3	0.07	3.99	2,827 ***	-0.23 ***	0.99	3,480	6.90
		Mod.4	0.15 **	0.50 **	2,656 ***	0.77	0.96	22,600	12.23
7	8	Mod.1	0.17 ***	0.48 **	2,822 ***		0.97	19,400	15.69
		Mod.2	0.16 ***	0.69 **	14,489	-0.32 *	0.99	9,000	11.49
		Mod.3	0.19	2.25	2,989 ***	-0.21 **	0.99	2,750	4.60
		Mod.4	0.17 **	0.48 **	2,844 **	0.98	0.99	19,120	15.80
8	8	Mod.1	0.18 ***	0.45 **	2,583 ***		0.98	12,100	13.08
		Mod.2	0.18 **	0.52 **	5,672	-0.15	0.98	10,600	16.64
		Mod.3	0.25 **	2.06 **	2,715 ***	-0.19 ***	0.99	227	2.30
		Mod.4	0.17 **	0.48 **	2,608 ***	1.53	0.98	10,200	9.85

Table 4A.1.
Parameter estimates for Spain (continued)

Movie (code)	Weeks	Model	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{M}$ (10^3)	$\hat{\delta}_1$, $\hat{\delta}_2$ or $\hat{\delta}_3$	r	SSR (10^6)	MAPE
9	7	Mod.1	0.24 ***	0.40 **	1,905 ***		0.98	5,460	11.74
		Mod.2	0.23 **	0.53 **	4,529	-0.17	0.99	3,010	6.90
		Mod.3	Do not converge						
		Mod.4	0.24 **	0.41 *	1,888 **	-1.12	0.98	5,260	10.68
10	7	Mod.1	0.12 **	0.46 **	562 ***		0.94	265	10.27
		Mod.2	Do not converge						
		Mod.3	0.21 ***	1.45 **	655 ***	-0.29	0.99	30	2.88
		Mod.4	0.11 **	0.43 **	575 ***	0.78	0.97	225	7.30
11	15	Mod.1	0.09 ***	0.26 ***	3,006 ***		0.95	23,100	20.06
		Mod.2	0.09 ***	0.33 ***	9,212	-0.24	0.96	18,700	16.02
		Mod.3	0.20 **	0.72 **	3,149 ***	-0.24 **	0.96	15,900	10.79
		Mod.4	0.09 ***	0.25 ***	3,011 ***	0.30	0.95	23,100	19.67
12	7	Mod.1	0.04	0.13	7,723		0.83	4,670	7.12
		Mod.2	Do not converge						
		Mod.3	Do not converge						
		Mod.4	0.04	0.14	6,968	-0.89	0.84	4,600	7.22
13	9	Mod.1	0.24 ***	0.40 **	2,040 ***		0.97	18,700	26.75
		Mod.2	0.23 **	0.56 **	3,094 **	-0.09	0.98	14,800	18.08
		Mod.3	0.05	5.22	2,080 **	-0.19 **	0.99	18,058	19.62
		Mod.4	0.23 **	0.40	2,065 **	1.21	0.97	7,391	23.26
14	19	Mod.1	0.05 ***	0.25 ***	3,257 ***		0.92	28,300	26.90
		Mod.2	0.04 ***	0.42 ***	5,832 ***	-0.15 ***	0.95	18,100	15.89
		Mod.3	0.06 ***	0.82 ***	3,364 ***	-0.26 ***	0.97	12,200	16.86
		Mod.4	0.03 ***	0.28 ***	3,299 ***	0.88 **	0.95	16,900	21.13
15	8	Mod.1	0.11 **	0.58 **	1,371 ***		0.88	15,500	24.85
		Mod.2	0.09	0.75	4,241	-0.25	0.88	14,800	22.33
		Mod.3	0.03	3.98 **	1,540 ***	-0.28	0.99	233	2.62
		Mod.4	0.07 **	0.52 **	1,435 ***	1.67 *	0.97	3,710	13.30
16	7	Mod.1	0.22 ***	0.49	1,919 ***		0.96	16,900	13.91
		Mod.2	0.21 **	0.71	3,138	-0.11	0.96	14,600	13.78
		Mod.3	Do not converge						
		Mod.4	0.21 **	0.52	1,949 **	0.76	0.96	15,800	14.49

Table 4A.1.
Parameter estimates for Spain (continued)

Movie (code)	Weeks	Model	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{M}$ (10^3)	$\hat{\delta}_1$, $\hat{\delta}_2$ or $\hat{\delta}_3$	r	SSR (10^6)	MAPE
17	7	Mod.1	0.08 **	0.49 *	2,155 ***		0.80	19,700	14.83
		Mod.2	0.12	0.32	497	0.29	0.83	16,600	13.80
		Mod.3	0.03	0.28	2,033 **	0.27	0.83	16,930	13.97
		Mod.4	0.08 *	0.47	2,175 **	0.05	0.80	19,600	14.67
18	7	Mod.1	0.25 **	0.42	1,556 ***		0.97	6,940	16.32
		Mod.2	0.25 **	0.66 **	3,132 **	-0.15	0.99	2,840	12.58
		Mod.3	Do not converge						
		Mod.4	0.25 **	0.43 **	1,557 **	0.13	0.97	6,926	16.61
19	7	Mod.1	0.22 **	0.57 **	1,724 ***		0.97	10,300	15.52
		Mod.2	0.21 **	0.65	2,284	-0.06	0.97	9,510	18.34
		Mod.3	Do not converge						
		Mod.4	Do not converge						
20	7	Mod.1	0.15 **	0.61 **	1,069 ***		0.98	1,510	11.58
		Mod.2	0.13 **	0.78 **	2,442 *	-0.18	0.99	655	8.43
		Mod.3	0.21 **	1.31 **	1,120 ***	-0.15 **	0.99	173	3.29
		Mod.4	0.15 **	0.58 **	1,076 ***	0.21	0.98	1,460	10.11
21	7	Mod.1	0.23 **	0.43 **	1,868 ***		0.98	6,160	13.54
		Mod.2	0.22 **	0.60 **	5,440	-0.22	0.99	2,780	6.28
		Mod.3	Do not converge						
		Mod.4	0.23 **	0.43 **	1,868 **	0.01 **	0.98	6,160	13.54

***: $p \leq 0.001$; **: $p \leq 0.05$; *: $p < 0.1$

Table 4A.2.
Parameter estimates for Spain, France and Italy.

					Spain							France							Italy						
Movie	W_S	W_F	W_I	Model	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{M}$ (10^3)	$\hat{\delta}_1$, $\hat{\delta}_2$ or $\hat{\delta}_3$	r	SSR (10^6)	MAPE	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{M}$ (10^3)	$\hat{\delta}_1$, $\hat{\delta}_2$ or $\hat{\delta}_3$	r	SSR (10^6)	MAPE	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{M}$ (10^3)	$\hat{\delta}_1$, $\hat{\delta}_2$ or $\hat{\delta}_3$	r	SSR (10^6)	MAPE
5	10	9	8	1	0.11***	0.24***	3,818***		0.92	29,000	15.82	0.15	-0.13	3,292		0.93	15,047	14.16	0.12***	0.46***	1,652***		0.99	1,090	8.46
				2	0.09**	0.14	1,153	0.26	0.94	22,200	10.10	Do not converge							0.18***	0.53**	1,957**	-0.04	0.99	831	6.13
				3	0.0002	0.11	4,435	1.17	0.94	22,000	10.06	Do not converge							0.28**	0.83**	1,676***	-0.12*	0.99	708	6.89
				4	0.10***	0.20*	4,153***	0.84	0.96	25,400	11.06	0.19	-0.11	2,719	-7.25	0.94	11,533	13.10	0.17***	0.44***	1,679***	0.34**	0.99	264	5.39
6	8	8	7	1	0.15***	0.51**	2,632***		0.96	22,800	13.11	0.27***	0.11*	3,153***		0.99	2,910	7.07	0.25***	0.48**	1,758***		0.99	2,270	10.64
				2	0.14**	0.67**	9,265	-0.25	0.97	17,600	10.61	0.27***	0.07	2,042	0.08	0.99	2,420	6.01	0.24***	0.63**	2,363**	-0.06	0.99	1,370	8.25
				3	0.07	3.98	2,827***	-0.23***	0.99	3,480	6.90	Do not converge							Do not converge						
				4	0.15**	0.50**	2,656***	0.77	0.96	22,600	12.23	0.28***	0.12*	3,119***	-0.49	0.99	2,710	7.25	0.24**	0.43**	1,805***	0.58	0.99	1,340	8.56
9	7	6	11	1	0.24***	0.40**	1,905***		0.98	5,460	11.74	0.17	-0.05	1,915		0.43	55,540	57.76	0.45***	0.36**	888***		0.99	1,150	56.62
				2	0.23**	0.53**	4,529	-0.17	0.99	3,010	6.90	Do not converge							0.41***	0.70***	1,007***	-0.04**	0.99	389	40.45
				3	Do not converge							Do not converge							Do not converge						
				4	0.24**	0.41*	1,888**	-1.12	0.98	5,260	10.68	0.24	-0.18	1,528	-3.71	0.80	27,923	53.58	0.42***	0.39***	903***	0.99***	0.99	249	23.16
13	9	6	7	1	0.24***	0.40**	2,040***		0.97	18,700	26.75	0.28**	0.42**	1,756***		0.99	3,450	9.09	0.16**	0.61***	1,369***		0.94	11,700	20.09
				2	0.23**	0.56**	3,094**	-0.09	0.98	14,800	18.08	0.28**	0.41	1,633	0.01	0.99	3,440	9.21	0.16**	0.55	1,136	0.04	0.94	11,500	17.46
				3	0.05	5.22	2,080**	-0.19**	0.99	18,058	19.62	0.50	0.97	1,795**	-0.10	0.99	3,080	11.45	Do not converge						
				4	0.23**	0.40	2,065**	1.21	0.97	7,391	23.26	0.28**	0.35	1,813**	1.17	0.99	2,640	11.54	0.16**	0.52	1,504**	1.52	0.95	9,120	27.86
14	19	13	10	1	0.05***	0.25***	3,257***		0.92	28,300	26.90	0.14***	0.12	2,060***		0.94	12,100	15.98	0.17***	0.36**	1,454***		0.96	8,120	17.68
				2	0.04***	0.43***	5,832***	-0.15***	0.95	18,100	15.89	Do not converge							0.17***	0.42*	1,672**	-0.04	0.96	7,970	18.70
				3	0.06***	0.82***	3,364***	-0.26***	0.97	12,200	16.86	0.36	0.51	2,106***	-0.25*	0.95	18,000	15.46	0.01	0.19**	1,472***	0.62*	0.98	5,240	15.06
				4	0.03***	0.28***	3,299***	0.88**	0.95	16,900	21.13	0.11***	0.12**	2,113***	0.99**	0.96	6,870	13.16	0.14***	0.42**	1,476***	0.66**	0.99	2,990	13.08
20	7	10	6	1	0.15**	0.61**	1,069***		0.98	1,510	11.58	0.19***	0.03	2,405***		0.98	4,040	8.45	0.15**	0.49**	743***		0.98	339	4.95
				2	0.13**	0.78**	2,442*	-0.18	0.99	655	8.43	0.19***	0.02	2,169	0.02	0.98	4,040	8.52	0.15**	0.46	617	0.05	0.98	331	5.04
				3	0.21**	1.31**	1,120***	-0.15**	0.99	173	3.29	0.09	0.01	2,436**	0.11	0.98	4,013	12.75	Do not converge						
				4	0.15**	0.58**	1,076***	0.21	0.98	1,460	10.11	0.18***	0.01*	2,494***	0.57	0.99	3,250	9.25	0.13**	0.42**	803***	0.78**	0.99	18	1.47

W_S: length of the life cycle of the movie in weeks in Spain; W_F: length of the life cycle of the movie in weeks in France; W_I: length of the life cycle of the movie in weeks in Italy;
***: $p \leq 0.001$; **: $p \leq 0.05$; *: $p < 0.1$

Chapter 5

Diffusion of franchising in Spain

5.1. Introduction

In this study we consider the diffusion of an organizational innovation, namely franchising. This organizational form creates thousands of jobs and generates a turnover of millions of euros. In Spain provisional data for 2004 puts the level of turnover at 15,017 million euros and the jobs (directly and indirectly) generated at 309,000 (Franquiciashoy, 2004). These figures reveal the importance of franchising for managers in Spain.

In this study we consider the diffusion of franchising as an organizational innovation and hence, we focus on the innovation at the level of the firm. We use diffusion modeling to analyze the diffusion of franchising among firms as an organizational innovation from the point of view of the franchisors. Although there are previous studies, such as Nevers (1972), that analyze the diffusion of franchising at the franchisee level (i.e. intra-firm diffusion), there are no previous studies at the franchisor level (i.e. inter-firm diffusion). The adoption of an innovation at the level of the firm is conceived as a means of changing an organization either as a response to changes in the external environment or as an anticipatory action to influence the environment (Damanpour, 1991, 1996; Waarts, Van Everdingen and Van Hillegersberg, 2002).

Any firm that intends to survive must submit itself to a process of evolution directing its efforts not only to the development of new products (goods or services), but also to the renovation of its organizational form, namely organizational innovation[1]. The implementation of organizational innovations often implies important changes in functions, tasks, responsibilities, systems and cultures that are difficult to understand and to apply (Mahajan, Sharma and Bettis, 1988; Meyers, Sivakumar and Nakata, 1999). Examples of organizational innovations are

[1] See Damanpour (1991), Wolfe (1994), Gatignon, Tushman, Smith and Anderson (2002) for research on and contributions to organizational innovations.

the creation of subsidiaries, new divisions, joint ventures, partnerships and franchising. We define franchising as "a system of commercialization of products and/or services and/or technologies based on a close collaboration among companies that are legally and economically different and independent, the franchisor and his/her individual franchisees. The franchisor gives his/her franchisees the right, and imposes the obligation of exploiting a firm in conformity with the franchisor's concept. The right given authorizes and obliges the franchisee, in exchange for a direct or indirect financial contribution, to use the trademark of the products and/or services, the "know-how" and the rest of the rights of intellectual property, sustained by the continuous benefit of commercial and/or technical attendance within the frame and along the time of the written contract of franchise" (Deontological European Code of Franchising). The contracts of franchise are identified in literature as hybrid forms of economical organization (Rubin, 1978; Mathewson and Winter, 1985; Norton, 1988).

In this study we apply diffusion models to analyze the diffusion of franchising, as organizational innovation, in Spain during the period 1974-1999. We follow a 4-steps procedure. First, we briefly review diffusion models that have been developed in marketing. Then we discuss examples of studies that consider the diffusion of organizational innovations[2]. We use two sets of models to obtain an appropriate description of the diffusion process of franchising. The first set of models is used to test whether imitation in the adoption of franchising is structural or random[3]. In this respect we follow Mahajan, Sharma and Bettis (1988) who, focusing on organizational innovations, question the imitation hypothesis behind the classical diffusion models. The second set of models is used to select the most appropriate diffusion model given that there is imitation and that the imitation is not random. We introduce the data and provide empirical evidence for an appropriate model to analyze the diffusion process of franchising in Spain. Finally, the outcomes are interpreted and discussed.

5.2. Modeling the diffusion of innovations

Diffusion models describe the spread of an innovation among a set of prospective adopters over time. A diffusion model depicts successive increases in

[2] Despite the wide application of diffusion models to consumer innovations, their use in industrial/business settings is very limited (Kahn, 2002).

[3] When we say "random", we mean that it is not possible to find a mathematical specification to explain imitation behavior because only randomness can explain it. However, we use "structural" to show that this mathematical specification can be found.

the number of adopters and predicts the continued development of a diffusion process (Mahajan, Muller and Bass, 1993).

We start from the diffusion model proposed by Bass (1969). It is the most parsimonious aggregated diffusion model suggested in the marketing literature (Parker, 1994) and the most accepted in the field of diffusion of innovations[4]. It can be specified as:

$$n(t) = \frac{dN(t)}{dt} = \beta_1 \left[M - N(t) \right] + \beta_2 \frac{N(t)}{M} \left[M - N(t) \right] \tag{5.1}$$

where $N(t)$ is the cumulative number of adopters at time t, M is the total number of potential adopters (e.g., consumers or firms -agents- who ultimately adopt), $n(t)$ is the non-cumulative number of adopters at time t, β_1 represents the influence of a "change agent" in the diffusion process, which may capture any influence other than that from previous adopters (innovative behavior), and β_2 can be interpreted as the word-of-mouth effect of previous adopters upon potential adopters (imitating behavior).

The first term in Equation (5.1) represents adoptions that are not influenced by the number of effective adopters. The second term represents adoptions that are influenced by the number of previous adopters. This model is a mixed influence model. An increase in $N(t)$ is modeled as the sum of two terms, each having its own interpretation. For $\beta_1 = 0$ we have the internal influence model or the Mansfield (1961) model, which does not account for external influence. For $\beta_2 = 0$, we have the external influence model or the Coleman (1966) model.

Although both the parameters β_1 ($\beta_1 \geq 0$) and β_2 ($\beta_2 \geq 0$) affect the shape of the diffusion curve, their impact is different. The parameter β_1 affects mainly the intercept of the model and, therefore, the necessary time to reach the maximum number of adoptions. Thus, the larger β_1 is, the sooner this moment arrives. The parameter β_2 affects mainly the magnitude of adoptions per period; so the larger β_2 ($\beta_2 \geq 0$) is, the greater the number of adoptions will be. Apart from being positive, it is expected that $\beta_1 < \beta_2$, reflecting that the forces behind the innovating behavior are of less intensity than the ones behind the imitating behavior: see also Figure 5.1.

[4] See also Sultan, Farley and Lehmann (1990) and Mahajan, Muller and Bass (1993).

Figure 5.1.
The incremental effect of the coefficients β_1 and β_2 on diffusion curves, holding others in the model constant

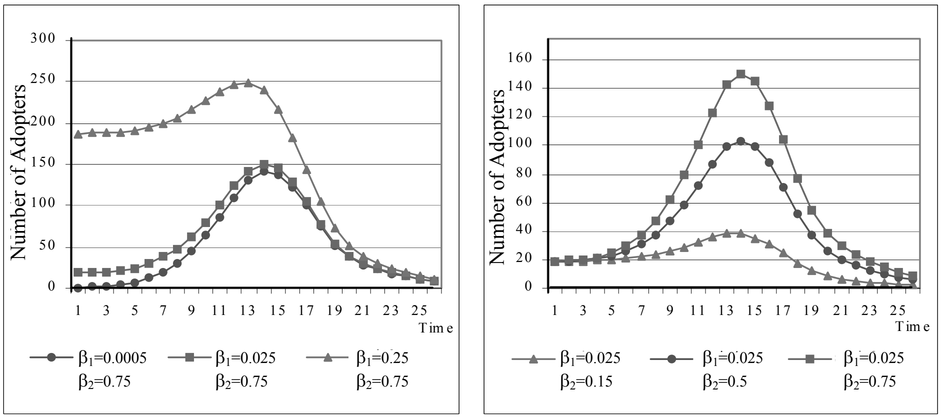


Figure 5.1 starts at t=1

There are several refinements and extensions of the Bass diffusion model[5]. Jeuland (1981) proposes a mixed influence model in which the effective potential market, $[M\text{-}N(t)]$, obtains an exponent: β_3 ($\beta_3 \geq 0$), where β_3 accounts for the heterogeneity of the population of potential adopters. The parameter allows for differences among adopters in their propensities to adopt an innovation. When adopters are firms, these differences are referred to objectives, strategies, abilities to change, and so on. Hence we get:

$$n(t) = \frac{dN(t)}{dt} = \left(\beta_1 + \beta_2 \frac{N(t)}{M}\right)\left[M - N(t)\right]^{(1+\beta_3)}. \tag{5.2}$$

The incorporation of the parameter β_3 affects both the external and the internal influence. That is,

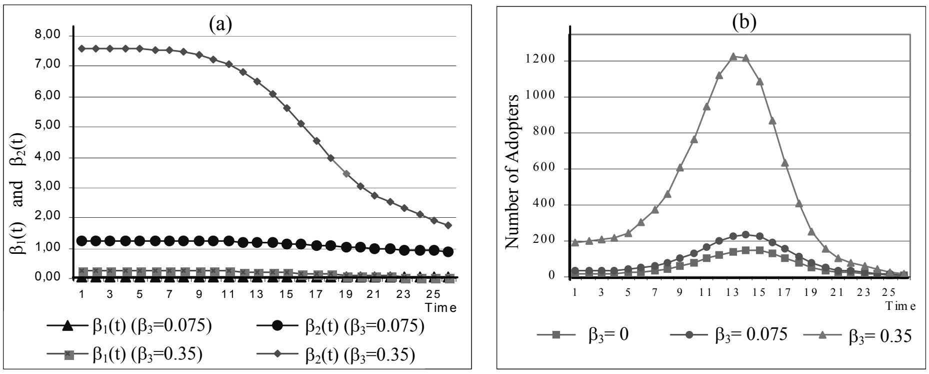
$$\beta_i(t) = \beta_i \left[M - N(t)\right]^{\beta_3},\ i = 1, 2 \tag{5.3}$$

where $\beta_1(t)$ and $\beta_2(t)$ represent the external and the internal influence, respectively. The $\beta_i(t)$ change over time in this way. As $\left[\frac{d\beta_i(t)}{dN(t)}\right] = -\beta_i\beta_3\left[M - N(t)\right]^{\beta_3 - 1} < 0$ with i = 1, 2 and $\beta_3 > 0$, $\beta_1(t)$ and $\beta_2(t)$ will decrease in the passage of time (see Figure 5.2a). Furthermore, the larger β_3 is, the

[5] See also Mahajan, Muller and Bass (1993), Parker (1993), Mahajan, Muller and Wind (2000).

sooner the time to peak arrives and the larger the number of adoptions will be. This is illustrated in Figure 5.2b for different values of β_3.

Figure 5.2.
(a) The time-varying coefficients of external, $\beta_1(t)$, and internal, $\beta_2(t)$, influence (Assumption: β_1= 0.025 and β_2=0.75).
(b) Effect of the coefficient of heterogeneity, β_3, on diffusion curves.



Figures 2a and 2b start at t=1

Easingwood, Mahajan and Muller (1981, 1983) developed models in which the impact of the word-of-mouth effect on potential adopters is flexible and may increase, decrease or remain constant over time. The Non-Uniform Influence Innovation Diffusion model (NUI) of Easingwood, Mahajan and Muller (1983) is a mixed influence model where the parameter of internal influence systematically varies over time as a function of penetration level. That is,

$$\beta_2(t) = \beta_2 \left[\frac{N(t)}{M} \right]^{\beta_4} \tag{5.4}$$

where β_4 ($\beta_4 \geq -1$) is the parameter of non-uniform influence. Substituting β_2 for $\beta_2(t)$ in Equation (5.1), and then Equation (5.4) into Equation (5.1) we get

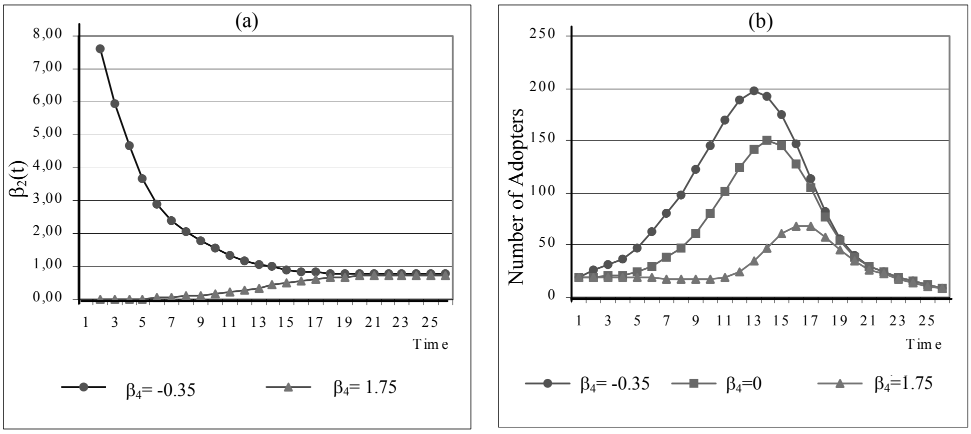
$$n(t) = \frac{dN(t)}{M} = \left(\beta_1 + \beta_2 \left(\frac{N(t)}{M} \right)^{(1+\beta_4)} \right) \left[M - N(t) \right]. \tag{5.5}$$

In the Non-Symmetric Responding Logistic model (NSRL) of Easingwood, Mahajan and Muller (1981) the parameter of external influence (β_1) is zero. We may have two different situations:

(i) If $-1 < \beta_4 < 0$, $\beta_2(t)$ will fall with the passage of time ($\frac{d\beta_2(t)}{dN(t)} = \frac{\beta_2\beta_4}{M}\left[\frac{N(t)}{M}\right]^{\beta_4 - 1} < 0$) and the speed of the diffusion process will accelerate. As we can see in Figure 3a, the passage of time reduces $\beta_2(t)$, accelerating the diffusion process and showing a diffusion curve slanted towards the left: see Figure 5.3b.

(ii) If $\beta_4 > 0$, $\beta_2(t)$ will grow with the passage of time ($\frac{d\beta_2(t)}{dN(t)} = \frac{\beta_2\beta_4}{M}\left[\frac{N(t)}{M}\right]^{\beta_4 - 1} > 0$) and the speed of the diffusion process will reduce. As we can see in Figure 3a, the passage of time increases $\beta_2(t)$, decelerating the diffusion process and showing a diffusion curve slanted towards the right: see Figure 5.3b.

Figure 5.3.
(a) The time-varying word-of-mouth effect, $\beta_2(t)$ (Assumption: β_1= 0.025 and β_2=0.75).
(b) Effect of the nonuniform influence coefficient, β_4, on diffusion curves.



Figures 5.3a and 5.3b start at t=1

There are extensions of the Bass model that specify the potential market as a function of relevant variables that affect the potential market. Examples of these variables are the growth in the number of households (Mahajan and Peterson, 1978; Sharif and Ramanathan, 1981; Parker, 1993), price (Kamakura and Balasubramanian, 1988; Jain and Rao, 1990), number of retail outlets where the (new) product is available (Jones and Ritz, 1991), and so on.

The models shown in Equations (5.1), (5.2), (5.5), the NSRL model and their counterparts with a dynamic potential market, *M*(*t*), are nested in the following model (Parker, 1993):

$$n(t)=\frac{dN(t)}{dt}=\left(\beta_1+\beta_2\left(\frac{N(t)}{M(t)}\right)^{(1+\beta_4)}\right)\left[M(t)-N(t)\right]^{(1+\beta_3)}. \tag{5.6}$$

Table 5.1 summarizes these models. We return to these models in Section 5.

Table 5.1.
Summary table.

Reference	Model equation	Applications
Naïve model		
Bass model (1969)	$n(t)=\left(\beta_1+\beta_2\left(\frac{N(t)}{M}\right)\right)\left[M-N(t)\right]$	Consumer durables
Extension to...		
...Heterogeneity		
Jeuland (1981)	$n(t)=\left(\beta_1+\beta_2\left(\frac{N(t)}{M}\right)\right)\left[M-N(t)\right]^{(1+\beta_3)}$	Consumer durables
...Non-uniform Influence		
Easingwood, Mahajan and Muller -NSRL- (1981)	$n(t)=\left(\beta_2\left(\frac{N(t)}{M}\right)^{(1+\beta_4)}\right)\left[M-N(t)\right]$	Medical innovations
Easingwood, Mahajan and Muller -NUI- (1983)	$n(t)=\left(\beta_1+\beta_2\left(\frac{N(t)}{M}\right)^{(1+\beta_4)}\right)\left[M-N(t)\right]$	Consumer durables
...Heterogeneity and Non-uniform Influence		
Parker (1993)	$n(t)=\left(\beta_1+\beta_2\left(\frac{N(t)}{M}\right)^{(1+\beta_4)}\right)\left[M-N(t)\right]^{(1+\beta_3)}$	Consumer durables

5.3. Diffusion of organizational innovations

The diffusion models discussed in the previous section refer to diffusions of consumer durables. The study of the diffusion of organizational innovations has its origins in the 1980s, with the studies of Teece (1980), Thompson (1983), Antonelli

(1985) and Mahajan, Sharma and Bettis (1988). With the exception of Antonelli (1985), these authors base their studies on the multidivisional form structure (M-Form). Antonelli (1985) analyses the diffusion of International Data Telecommunications (IDT).

Teece (1980) applies the diffusion model of internal influence of Mansfield (1961). His study allows him to conclude that the innovation analyzed is subjected to a diffusion process that follows a logistic function similar to that described by the diffusion of certain technological innovations.

Thompson (1983) applies different functional forms to the adoption data of organizational innovation. He calibrated a cumulative normal, a logarithmic reciprocal, a cumulated log-normal and a logistic model. The results show the superiority of the logistic model and indicate that the model of internal influence (based on contagion) is appropriated in this context.

Antonelli (1985) analyses the structural and technological determinants of the diffusion of IDT (intra-firm and inter-firm) seen by him as an important innovation both technologically and organizationally. Insofar as this innovation implies changes in the organizational structure of the firm, this study is characterized in the area of the diffusion of business organizational innovations.

The imitation hypothesis has been accepted in many studies on the diffusion of organizational innovations; compare e.g. Mansfield (1961, 1963), Romeo (1975, 1977), Teece (1980), Thompson (1983), Hannan and McDowel (1984). Mahajan, Sharma and Bettis (1988), however, question its validity. The imitation hypothesis maintains that the ratio of inter-firm diffusion is governed by imitative behavior between adopters and non-adopters. Mahajan, Sharma and Bettis re-examine the imitation hypothesis and compare the models of Coleman (Coleman, Katz and Menzel, 1966) (exponential), Mansfield (1961) (S-type), Bass (1969) (S-type) and the square form (S-type) with a random walk process. Their results question the suitability of the imitation hypothesis, as it can not reject the hypothesis that the adoption of the organizational innovation analyzed is a random walk process.

In this study we analyze franchising as an organizational innovation. Franchising has its origins in the automobile industry in the United States in 1929, when the *General Motors* Company constructed the first franchise contract. Also, in the same year, in the textile sector in France, the wool factory *La Lainière de Roubaix* became the pioneer in franchising contracts in Europe when it opened the franchisee shops *Pingouin*. The real development in Europe starts in the 1970s along with the economic crisis originated by the petrol crisis in 1973. Although, the franchising system appears in the 1950s in Spain [*Rodier* in 1957, *Spar Española* in 1959, *Pingouin Esmeralda* in 1961, *Prenatal* in 1963 (Casa and Casabo, 1989)], it is from 1974 that franchising is gradually adopted by Spanish firms[6]. A slow diffusion process for this organizational innovation can be expected given the large numbers of organizational possibilities (Cheung, 1969; Rubin, 1978; Mariti and Smiley, 1983; Mathewson and Winter, 1985; Norton, 1988) and the late legal regulation of franchising in Spain[7].

The data provided by the Spanish Association of Franchisors demonstrate that between 1997 and 1999 there is an increase of more than 26 percent in the number of franchisors, reaching a total of 529 franchisors in 1999. That accounts for more than 23,000 franchisees and has created more than 93,000 jobs (directly and indirectly) generating a turnover in excess than 4,207 million euros. These figures show the extraordinary expansion of this managerial organization. The increasing number of attendants (expositors and visitors) at franchising fairs in Spain confirms the higher level of interest emerging from Spanish managers for this managerial mode[8]. It reveals how the Spanish companies[9] have considered changing their organizational structure in connection with the distribution of their products by means of franchising. Franchising has become the preferred option of business growth for many companies vis-à-vis opposed to other business alternatives (Fulop and Forward, 1997). The organizational benefits brought by franchising to the adopting company contribute to improvements in management and to distribution channels. We know that franchising is a mechanism that reduces the divergence of interest between the parties (franchisor and franchisee), reducing agency problems

[6] There is not a left censoring problem in our data given that: the study period starts in 1974, since although we only know of a few firms using this innovation in a sporadic manner as mentioned before; it is from 1974 that the innovation is, in fact, gradually introduced in Spain.

[7] The first steps towards elaborating specific regulation of franchising in Spain happened in 1996. Article 62 from Law 7/1996, January 15th, about Retailing Business Regulation, referring to the commercial activity in franchising was something new in the Spanish Law. This article opens the regulation development of the basic conditions for franchising, as well as the creation of the Register of Franchisors. Before this law, we had on one side the Regulation of the Commission of the EEC nº 4087/88, November 30th 1988, related to the application of point 3 of the article 85 from the Treaty Franchising Contracts, which went into effect on February 1st 1989; and on the other side, the European Code of Franchising applicable in Spain went into effect January 1st 1991, and it was assumed by Spanish Association of Franchisors.

[8] El Salón Internacional de la Franquicia (SIF) – considered the most important fair of the world of franchise-, was created in 1990 with 65 expositors and 3,282 visitors, and reaches 398 expositors and 30,225 visitors in its 1999-edition.

[9] There is not a specific type of company interested in franchising, we can find franchisors in different sectors of activity, such as: Food; Gifts, Decorations and Furniture; Second Hand Goods; Audio, Music, Video, Photography and Optics; Clothing, Fashion and Accessories, Sports; Cosmetics, Perfumery; Diet and medicines; Computers; Gardening, DIY, Hardware and Pets; Jewellery; Stationary; Leisure and Entertainment Goods; Catering, Restaurants, Bakers, Cake Makers and Ice Cream Bars; Services includes: Travel Agents; Estate Agents; Business Advisors and services to companies and/or individuals; Cars sector; Printing and Sign Making; Cleaning and Repair of Clothing; Cleaning and Restoration of Buildings; Leisure; Recycling; Telecommunications; Transport and Deliveries; Health and Beauty Treatments; Vending.

and allowing the possibility of reaching common goals, such as the maximization of the present value of the franchised unit. The franchisee, as a business person invests resources in the business, allowing the franchising company access to the resources necessary for expansion. Large companies can also benefit through franchising from the flexibility of small businesses. As franchisees own the residual rights, they put maximum effort into sales, cost control, quality management and provide a high level of customer service. The franchising company's control over the compliance of business directives by the franchisees is clearly defined through the contractual agreements between the franchisor and the franchisee. Therefore, without the franchisee losing autonomy, the franchising company is assured of a high level of organizational and operative control over its business units. This characteristic of franchising allows the establishment and maintenance of certain corporative standards that would be more difficult to achieve under a system of decentralized distribution (through intermediaries outside the franchising system as distributors or licensees) (Mendelsohn, 1992). As pointed out by Kaufmann (1996, p.5): "*there is strong theoretical support for franchising as an optimal organizational form. Given the correct set of contextual variables, franchising can take advantage of both economies of small scale (solving incentives issues) and economies of large scale (by combining and leveraging system-wide resources) at the same time*".

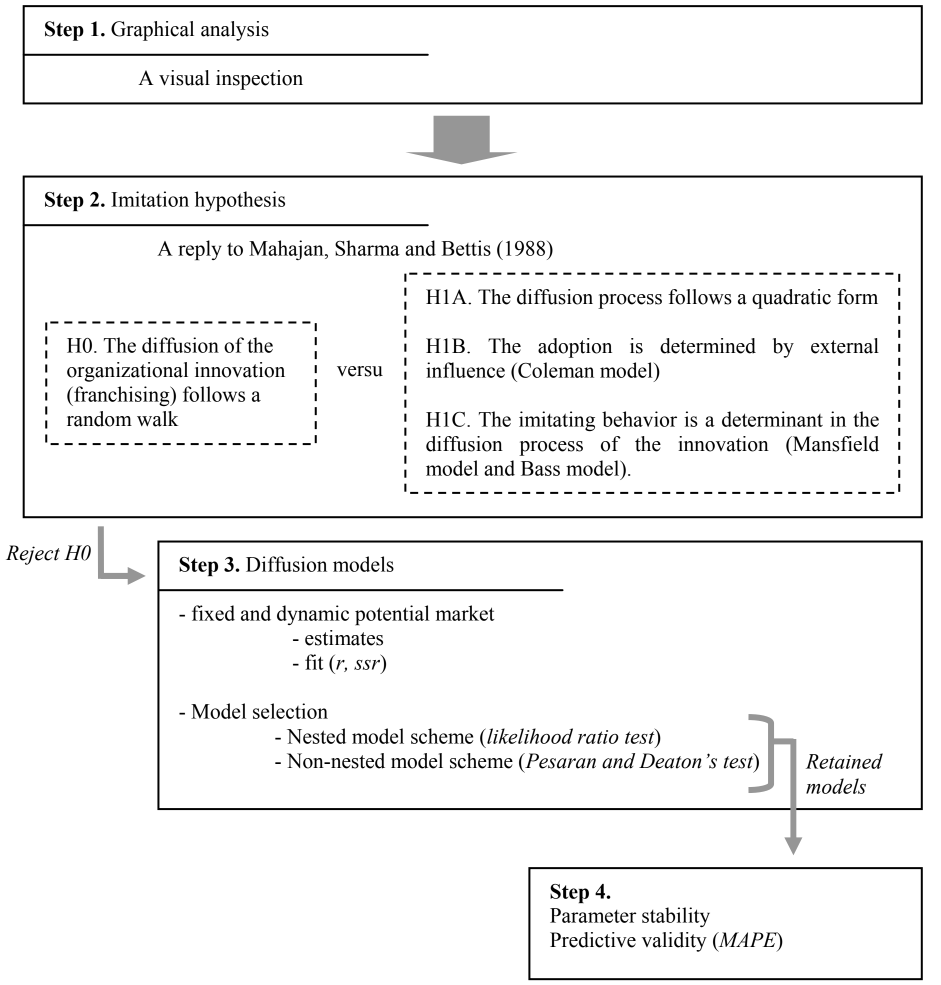
5.4. Methodology

The methodology that we propose consists of four steps (see Figure 5.4): (1) a graphical analysis of the diffusion curve; (2) a test to conclude whether there is imitation or not; (3) the selection of one or more diffusion models given that there is imitation; and (4) the ultimate choice of the most appropriate diffusion model using stability and predictive validity measures.

Graphical analysis of the adoption data indicates whether it is convenient to carry out an analysis of diffusion (employing diffusion models). Before selecting the most appropriate diffusion model, we have to demonstrate that the forces of adopter's behavior (innovative and imitating behavior), and not only randomness govern this diffusion process. Otherwise the employment of diffusion models (or any model) has no sense. For that reason we include step 2.

Steps 1 and 4 speak for themselves. In this section we discuss steps 2 and 3 in more detail.

Figure 5.4.
Steps of the empirical analysis.



Step 2: Convenience of the hypothesis of imitation

We first test whether there is an imitation process or not[10]. In this respect we follow Mahajan, Sharma and Bettis (1988) who test the null hypothesis: the diffusion is a random walk vis-à-vis alternative hypotheses (H1A, H1B and H1C).

If the diffusion of an (organizational) innovation follows a random walk, we have

H0. $x(t) = x(t-1) + u(t)$ (5.7)

where $x(t) = N(t) - N(t-1)$ is the number of adopters in period t, $N(t)$ is the cumulative number of adopters at time t and $u(t)$ is a disturbance term with zero mean, which is not correlated with $u(t-k)$ $\forall \mathrm{k} \neq 0$.

Remark: we now use $x(t)$ instead of $n(t)$ where $x(t)$ is the number of adopters in period t, and $n(t)$ is the non-cumulative number of adopters at t. Hence we now use difference equations instead of differential equations.

The alternative hypotheses assume that:

- H1A. The diffusion process follows a quadratic form;
- H1B. The adoption is determined by external influence (Coleman model);
- H1C. The imitating behavior is a determinant in the diffusion process of an innovation (Mansfield model and Bass model).

If we assume that the diffusion process follows a quadratic form we have

H1A. $x(t) = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + v(t)$ (5.8)

where $\alpha_1 > 0$, $\alpha_2 < 0$ and $v(t)$ is a disturbance term. Equation (5.8) can be rewritten by subtracting $x(t\text{-}1)$ from $x(t)$. Hence we get:

H1A. $x(t) = \lambda_0 + \lambda_1 t + \lambda_2 x(t-1) + v(t)$ (5.9)

where $\lambda_0 = (\alpha_1\text{-}\alpha_2) > 0$, $\lambda_1 = 2\alpha_2 < 0$, $\lambda_2 = 1$ and $v(t)$ is a disturbance term.

If we reformulate Equation (5.1) with $\beta_2 = 0$ as a difference equation, we get:

H1B. $x(t) = \lambda_2 x(t-1) + w(t)$ (5.10)

where $\lambda_2 = (1\text{-}\beta_1) < 1$ and $w(t)$ is a disturbance term.

We consider two alternative specifications that account for adoptions caused by imitation viz. the Mansfield model -Equation (5.1) with $\beta_1 = 0$- and the Bass model -Equation (5.1)-:

H1C. Mansfield: $$\frac{dN(t)}{dt} = \beta_2 \frac{N(t)}{M}\left[M - N(t)\right] \quad (5.11)$$

Bass: $$\frac{dN(t)}{dt} = \left(\beta_1 + \beta_2 \frac{N(t)}{M}\right)\left[M - N(t)\right]. \quad (5.12)$$

[10] Imitation, sociocontagion or word-of-mouth has been found to be the most important factor that characterizes the diffusion process of an innovation (Bass, 1969; Moore, 1995; Kumar and Krishnan, 2002).

These models are rewritten as:

$$x(t) = \lambda_2 x(t-1) + \lambda_3 NN(t-1) + \varepsilon(t) \tag{5.13}$$

where $\lambda_2 > 1$, $\lambda_3 < 0$, $NN(t-1) = N(t-1)^2 - N(t-2)^2$ and $\varepsilon(t)$ is a disturbance term. In the Mansfield model $\beta_1 = 0$, $\beta_2 > 0 \Rightarrow \lambda_2 = (\beta_2+1) > 1$ and $\lambda_3 = (-\beta_2/M) < 0$, and in the Bass model $\beta_1 > 0$, $\beta_2 > 0$ and $\beta_1 >> \beta_2$ and hence $\lambda_2 = (\beta_2 - \beta_1+1) > 1$ and $\lambda_3 = (-\beta_2/M) < 0$.

Table 5.2 summarizes the null and alternative hypotheses.

Table 5.2.
Convenience of the hypothesis of imitation

Hypothesis	Equivalencies between the parameters of the models and the parameters of the similar regressions	Expected signs and values of the parameters λ_0	λ_1	λ_2	λ_3	Values of the parameters to accept H_0
H0				1		
H1A	$\lambda_0 = \alpha_1 - \alpha_2$ $\lambda_1 = 2\alpha_2$ $\lambda_2 = 1$	>0	<0	1		$\lambda_0 = 0$, $\lambda_1 = 0$
H1B	$\lambda_2 = (1-\beta_1)$			<1		$\lambda_2 = 1$
H1C	*Mansfield model:* $\lambda_2 = 1+\beta_2$ $\lambda_3 = -(\beta_2/M)$ *Bass model:* $\lambda_2 = 1+\beta_2 - \beta_1$ $\lambda_3 = -(\beta_1/M)$			>1	<0	$\lambda_2 = 1$, $\lambda_3 = 0$

Step 3: Selection of a diffusion model given that there is imitation

We consider eight diffusion models with a fixed potential market: $M(t)=M$. These models are specified in Table 5.3. The models are well-known diffusion models, except models “3” and “6”, which are combinations of existing models. Model “1” coincides with the model of Parker (1993). Model “2” is the NUI model -Equation (5.5)-, model “4” the Jeuland model -Equation (5.2)-, model “5” the NSRL model, model “7” the Bass model -Equation (5.1)- and model “8” is the Mansfield model. Models “1”–“8” all have their counterparts with a dynamic potential market[11]. In the application it is assumed that for these models

$$M = M(t) = \beta_5 E(t) \tag{5.14}$$

where $E(t)$ is the total number of Spanish firms that could adopt the innovation at least in principle, and $0 < \beta_5 < 1$. Small estimated values of β_5 indicate few firms will eventually adopt franchising as an organizational innovation, while values of β_5 that approach 1 indicate the opposite.

[11] Examples of models with dynamic potential market are Chow (1967), Dodson and Muller (1978), Lackman (1978), Mahajan and Peterson (1978, 1979), Sharif and Ramanathan (1981), Kamakura and Balasubramanian (1988), Jain and Rao (1990), Parker (1992), Bass, Krishnan and Jain (1994), Polo (1996) and Dekimpe, Parker and Sarvary (1998).

Table 5.3.
Diffusion models

Model 1 (Parker model) $$n(t) = \left(\beta_1 + \beta_2 \left(\frac{N(t)}{M} \right)^{(1+\beta_4)} \right) \left[M - N(t) \right]^{(1+\beta_3)}$$	Model 5 (NSRL model) $$n(t) = \left(\beta_2 \left(\frac{N(t)}{M} \right)^{(1+\beta_4)} \right) \left[M - N(t) \right]$$
Model 2 (NUI model) $$n(t) = \left(\beta_1 + \beta_2 \left(\frac{N(t)}{M} \right)^{(1+\beta_4)} \right) \left[M - N(t) \right]$$	Model 6 $$n(t) = \beta_2 \left(\frac{N(t)}{M} \right) \left[M - N(t) \right]^{(1+\beta_3)}$$
Model 3 $$n(t) = \left(\beta_2 \left(\frac{N(t)}{M} \right)^{(1+\beta_4)} \right) \left[M - N(t) \right]^{(1+\beta_3)}$$	Model 7 (Bass model) $$n(t) = \left(\beta_1 + \beta_2 \left(\frac{N(t)}{M} \right) \right) \left[M - N(t) \right]$$
Model 4 (Jeuland model) $$n(t) = \left(\beta_1 + \beta_2 \left(\frac{N(t)}{M} \right) \right) \left[M - N(t) \right]^{(1+\beta_3)}$$	Model 8 (Mansfield model) $$n(t) = \left(\beta_2 \left(\frac{N(t)}{M} \right) \right) \left[M - N(t) \right]$$

Given the discussion in Section 5.2 we can summarize the expected signs of the parameter in the diffusion models: see Table 5.4.

Table 5.4.
Expected signs of the parameters of the diffusion models

Parameter	Expected sign
External influence	$\beta_1 \geq 0$
Internal influence	$\beta_2 \geq 0$
Heterogeneity	$\beta_3 \geq 0$
Non-uniform influence	$\beta_4 \geq -1$
Penetration of the potential market	$0 < \beta_5 < 1$

5.5. Sample, data and measurement of variables

There are no previous studies that analyze the diffusion of franchising among firms as an organizational innovation from the point of view of the franchisors. Nevers (1972) analyzed how a franchisor incorporates new franchise holders into its organization; i.e. intra-firm diffusion. In this study we investigate how franchising, seen as a form of business organization, is adopted by Spanish firms; i.e. inter-firm diffusion. Hence the adopting agents (franchisors) are Spanish firms. We consider the adoption of these firms for a period of 26 years: 1974-1999. We use annual data.

We obtained a list of franchisors from the Spanish Register of Franchisors. As registration to this Register is voluntary, there are far more franchisors than are registered. Hence, we collected additional data from three well-known franchising guides (Tormo Associated, Barbadillo Associated and the Spanish Association of Franchisors) as well as from the directories of the two most important franchising fairs in Spain (Expofranquicia and the International Salon of Franchising). The previous information was confirmed and also completed by directly contacting the franchisors by fax, telephone, post, e-mail or at the franchising fairs.

Data about the *dynamic potential market* variable in terms of the number of Spanish firms that could adopt franchising is obtained from the Commercial Register and publications of the National Institute of Statistics of Spain.

5.6. Empirical application

5.6.1. Step 1: Graphical analysis

A visual analysis[12] of the Spanish franchising data (Figures 5.5 and 5.6) shows a diffusion curve with a similar shape to other innovations discussed in the literature of diffusion of innovations (Mansfield, 1961; Nevers, 1972; Easingwood, 1988; Mahajan, Muller and Bass, 1990; Mahajan and Muller, 1994). Mansfield (1961) points out that the diffusion of a new technique is generally a rather slow process. The visual analysis confirms this and demonstrates that the diffusion of franchising has a rather slow start. The study performed by Mansfield (1961) shows that some firms take decades to adopt an innovation whereas others follow the innovator very quickly. His study shows that the number of years elapsing before half the firms had adopted an innovation oscillates between 0.9 and 15 years in the industries of bituminous coal and iron and steel. Easingwood (1988) considers several curves of diffusion for industrial and process innovations. He includes the (intra-firm)

[12] This visual inspection, made as a preliminary analysis, is intrinsically subjective.

diffusion of franchising as an innovation from Nevers's (1972) work and excludes consumer innovations of consumer products. The diffusion patterns that he presents differ in the number of years that an innovation takes to achieve a high penetration into the market. The number of years oscillates between 3.5 and 28.5 years. Figures 5 and 6 show the annual number of adopters and the cumulative number of adopters. From these figures it is clear that for franchising: (1) the cumulative number of adopters has probably not reached its maximum (*M*) yet given that the innovation seems to be in its growth stage (there are no post-peak data points in this stage); (2) the stage of introduction is very long. It took about 22 years to reach 50 per cent of the total number of adopters at the end of the period that we investigated (26 years). This very slow rate of adoption can be explained by the lack of legal regulations governing this organizational innovation until 1996.

Figure 5.5.
Number of adopters (franchisors) per time period

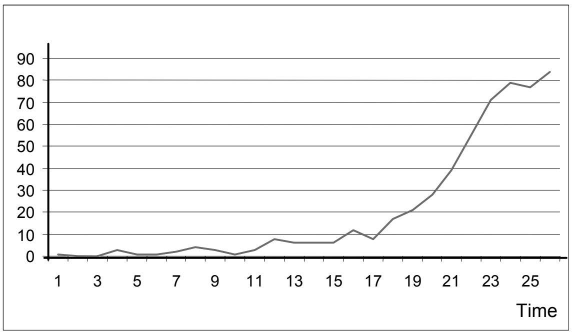


Figure 5.5 starts at t=1

Figure 5.6.
Cumulative number of adopters (franchisors)

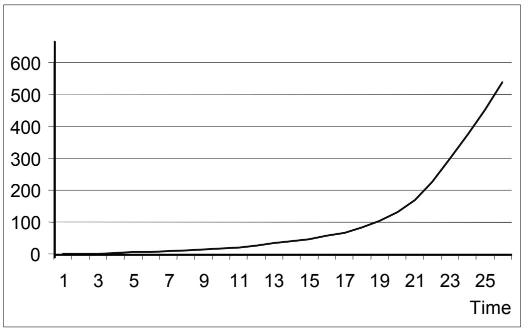


Figure 5.6 starts at t=1

5.6.2. Step 2: Testing the hypothesis of imitation

The models represented by Equations (5.9), (5.10) and (5.11) are estimated by Ordinary Least Squares. A comparison of the parameters in Table 5.5 with the corresponding parameters in Table 5.2 demonstrates that the Quadratic form -Equation (5.9)- does not have appropriate signs. The Coleman model -Equation (5.10)- has a parameter with a 0.99 probability of being larger than 1. Hence we have to reject H1B. The Mansfield-Bass models -Equations (5.11) and (5.12)- have the appropriate signs and magnitudes. The sum of the squared residuals (ssr) is the lowest of all these models and the χ^2-tests indicate that the null hypothesis of random walk has to be rejected and that imitation is one of the processes behind the adoption of franchising in Spain.

Table 5.5.
Parameter estimates of the Quadratic form, Coleman and Mansfield-Bass models -Equations (5.9), (5.10) and (5.11-5.12), respectively-

Models	Parameter estimates (*t* values between brackets)				r [a]	ssr	Test H_0	χ^2
	$\hat{\lambda}_0$	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_3$				
Quadratic Form	-2.29 (-1.80)	0.41^{**} (3.18)	1		0.99	490.10	$\lambda_0=0$, $\lambda_1=0$	14.03^{***}
Coleman			1.13^{***} (21.72)		0.99	619.93	$\lambda_2=1$	6.04^{*}
Mansfield-Bass			1.40^{***} (14.67)	-0.0005^{*} (-2.63)	0.99	400.69	$\lambda_2=1$ $\lambda_3=0$	27.60^{***}

[a] We use the correlation coefficient, r, which measures the correlation between the real and the estimated values of the dependent variables, because the Coleman and the Mansfield-Bass models do not have an intercept term (Judge et al., 1985, pp.30-31)
*** $p \leq 0.001$; ** $p \leq 0.01$; * $p \leq 0.05$.

5.6.3. Step 3: Selection of a diffusion model given that there is imitation

The eight diffusion models in Table 5.3 are estimated by non-linear estimation procedures (E-views and SAS-NLIN routine Marquardt) given the non-linearity of these models. Models where $N(t)$ can not be expressed as an explicit function of time are estimated directly from their original expression (models "1"-"6"). The models where $N(t)$ can be expressed as an explicit function of time (models "7" and "8") are estimated following Srinivasan and Mason (1986) and Van den Bulte and Lilien (1997). We consider eight diffusion models with fixed potential market -*M*- and eight with dynamic potential market -$M(t)$-. Models from each group are estimated and two different tests are performed to determine which model or models have the best statistical properties. Likelihood ratio tests are used for nested models. The test proposed by Cox (1961, 1962) and modified by Pesaran and Deaton (1978) (Judge et al., 1985) is used for non-nested models[13].

5.6.3.1. Fixed potential market

Table 5.6 shows the parameter estimates and a number of statistical criteria of the diffusion models with a fixed potential market.

Table 5.6.
Diffusion models with fixed potential market.

	Numbers of parameters	Parameter estimates (*t*-values between brackets)						
		$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$	$\hat{M}$	r	ssr
Model 2	4	0.001 (0.80)	0.64^{***} (7.13)		0.36^{**} (3.58)	658^{***} (14.86)	0.99	230.48
Model 4	4	-0.22 (-0.59)	22.27 (0.64)	-0.66^{*} (-2.28)		536^{***} (4.16)	0.99	388.05
Model 5	3		0.63^{***} (8.21)		0.33^{***} (4.23)	663^{***} (16.07)	0.99	233.33
Model 6	3		31.74 (0.90)	-0.74^{**} (-3.47)		513^{***} (5.18)	0.99	429.20
Model 7[a]	3	0.00002^{*} (2.53)	0.39^{***} (18.14)			852^{***} (15.95)	0.99	207.57
Model 8[a]	2		0.39^{***} (18.36)			852^{***} (15.92)	0.99	207.57

[a] estimated in a different way.
*** $p \leq 0.001$; ** $p \leq 0.01$; * $p \leq 0.05$; ° $p < 0.1$.

The models "1" and "3" are unstable (the non-linear estimation procedure does not supply parameter estimates that converge) and are not appropriate to describe the adoption of franchising. Overall, the other models show an acceptable level of fit to the data. The parameter estimates have the right signs except for the parameter β_1 of model "4" and the parameter β_3 of the models "4" and "6".

[13] See Parker and Gatignon (1994) for a detailed discussion in the field of diffusion models.

We perform the likelihood ratio test to select the most appropriate model[14] among the nested models "2" and "5". We also do not consider models "4" and "6", which have implausible parameter estimates. All the models where the parameter β_3 has been included show problems[15]. Following the likelihood ratio test, the restricted model (the most parsimonious model) is retained when there is no significant difference between the restricted and the unrestricted model. The outcome of the test is shown in Table 5.7.

Table 5.7.
Likelihood ratio test statistics (Fixed potential market)

Restricted Model (H_0)			Unrestricted Model (H_1)			χ^2 test		
Model	$T*\ln(ssr_0)$	p_0	Model	$T*\ln(ssr_1)$	p_1	-2lnN	$(p_1 - p_0)$	Conclusions
Models: 2, 5								
Model 5	141.76	3	Model 2	141.44	4	0.32	1	H_0 not rejected => Model 5

Likelihood ratio test: $\chi^2 = -(T*\ln(ssr_0) - T*\ln(ssr_1))$
p_0: number of parameters in the restricted model
p_1: number of parameters in the unrestricted model

From this table we deduce that model "5" has better statistical properties than model "2". Now we perform the Cox test to select the best model among the models "5", "7" and "8", which are non-nested models. This test discriminates between the two following non-nested models (Pesaran and Deaton, 1978; Judge et al., 1985):

$$H_0: (\textit{model a}) \qquad y = f(G,\gamma) + e, \quad e \sim N(0,\sigma^2 I) \tag{5.15}$$

$$H_1: (\textit{model b}) \qquad y = f(W,\omega) + u, \quad u \sim N(0,\mu^2 I) \tag{5.16}$$

where G and W are the variables to predict y, γ and ω are vectors of parameters, and e and u are random vectors. The test statistic is

$$C = \frac{T}{2}\left[\ln \hat{\mu}_m^2 - \ln \hat{\mu}^2\right] \tag{5.17}$$

where T is the number of observations, $\hat{\mu}_m^2$ is the maximum likelihood estimator[16] of μ^2, $\hat{\mu}^2 = \hat{\sigma}_m^2 + \frac{1}{T} ssr_1$, and ssr_1 is the sum of the squared residuals from regressing the fitted results of *model a* against the independent structure of *model b*. The C-statistic is normally distributed with mean zero and variance

[14] See, for example, Leeflang et al. (2000, Section 18.4.2).
[15] Compare also Parker (1993) who had the same problems.
[16] The estimates using the Marquardt non-linear estimation technique on SAS approach the Gauss maximum likelihood estimates (Parker and Gatignon, 1994).

$$V(C)=\frac{\hat{\sigma}_m^2}{\hat{\mu}^2}\left[u_1^{'}\left\{I_T - Z(\hat{\gamma})^{'}\left[Z(\hat{\gamma})^{'}Z(\hat{\gamma})\right]^{-1}Z(\hat{\gamma})\right\}u_1\right] \tag{5.18}$$

where u_1 is a vector of residuals that results from regressing the fitted results of *model a* against the independent structure of *model b*, and Z is a matrix with first order derivatives of *model a* evaluated at the maximum likelihood estimates of γ.

If the C-statistic is significant, the null hypothesis is rejected (*model a* is rejected), but it "does not imply that H_1 is accepted, since H_1 tested against H_0 may also be rejected" (Judge et al., 1985, pp. 883-884). As the Cox test is not symmetric, we have to repeat the test changing the hypothesis (i.e. H_0: *model b*, H_1 *model a*). Both models can be retained when there are no statistically significant differences between them, yielding inconclusive results. In this case, other criteria must be employed to select one of them. The outcomes of these tests are shown in Table 5.8.

Table 5.8.
Test of non-nested models with fixed potential market

		Alternative hypothesis (C-statistics)			Conclusions
		Model 5	Model 7	Model 8	(evaluated models => model retained)
Null hypothesis	Model 5	-	-5.90**	-5.90**	Mod 5, Mod 7 => both models Mod 5, Mod 8 => both models Mod 7, Mod 8 => both models
	Model 7	-3.57°	-	0.00	
	Model 8	-3.57°	0.00	-	

** $p \leq 0.01$; ° $p < 0.1$.

From this table we deduce that the models "5", "7" and "8" remain in competition. Therefore, we compare these models in step 4.

5.6.3.2. Dynamic potential market

The dynamic models "1", "3", "4" and "6" again give unstable outcomes. What remains are the outcomes of the models "2", "5", "7" and "8". Table 5.9 shows the parameter estimates and the values of a number of statistical validation criteria.

Table 5.9.
Results: the diffusion models with dynamic potential market

	Number of parameters	Parameter estimates (*t*-values in brackets) $\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_4$	$\hat{\beta}_5$	r	ssr
Model 2	4	-0.01 (-0.43)	0.98*** (7.65)	0.68** (2.87)	0.0004*** (25.58)	0.99	194.85
Model 5	3		1.01*** (10.64)	0.33*** (4.23)	0.0004*** (33.22)	0.99	196.99
Model 7[a]	3	0.0001* (2.08)	0.34*** (13.04)		0.001*** (14.80)	0.99	229.24
Model 8[a]	2		0.34*** (13.22)		0.001*** (14.79)	0.99	229.24

[a] estimated in a different way.
*** p ≤ 0.001; ** p ≤ 0.01; * p ≤ 0.05.

The results show that the models have a suitable fit to the data and all the parameter estimates have the right signs. $\hat{\beta}_1$ of model "2" is an exception; this parameter estimate is not statistically significant.

Again, we perform the likelihood ratio test between model "2" and "5", which are nested models. The outcome of this test is shown in Table 5.10.

Table 5.10.
Likelihood ratio test statistics (Dynamic potential market)

Restricted Model (H_0)			Unrestricted Model (H_1)			χ^2 test		
Model	T*ln(ssr_0)	p_0	Model	T*ln(ssr_1)	p_1	-2lnN	(p_1- p_0)	Conclusions
Models: 2, 5								
Model 5	137.36	3	Model 2	137.08	4	0.28	1	H_0 not rejected => Model 5

Likelihood ratio test: $\chi^2 = -(\ T^*\ln(ssr_0) - T^*\ln(ssr_1))$
p_0: number of parameters in the restricted model
p_1: number of parameters in the unrestricted model

From the outcomes of this test, we also have to conclude that model "5" is preferred to model "2". Now we perform the Cox test to select among the models "5", "7" and "8", which are non-nested models. The outcomes of these tests are shown in Table 5.11.

Table 5.11.
Test of non-nested models with dynamic potential market

		Alternative hypothesis (C-statistics)			Conclusions (evaluated models => model retained)
		Model 5	Model 7	Model 8	
Null hypothesis	Model 5	-	-6.10^{**}	-6.10^{**}	Mod 5, Mod 7 => both models Mod 5, Mod 8 => both models Mod 7, Mod 8 => both models
	Model 7	-9.43^{***}	-	0.00	
	Model 8	-9.43^{***}	0.00	-	

*** $p \leq 0.001$; ** $p \leq 0.01$

From this table we deduce that the models “5”, “7” and “8” remain in competition. We compare these models in step 4.

We are now able to investigate whether models “5”, “7” and “8” with a dynamic potential market have better statistical properties than models with fixed potential market. To answer this question, we also perform the Cox test. The outcomes of these tests are shown in Table 5.12.

Table 5.12.
Test of non-nested models with fixed and dynamic potential market (M and $M(t)$)

		Alternative hypothesis (C-statistics)						Conclusions (evaluated models => model retained)
		Model $5M$	Model $5M(t)$	Model $7M$	Model $7M(t)$	Model $8M$	Model $8M(t)$	
Null hypothesis	Model $5M$	-	-2.49^{***}					Mod $5M$, Mod $5M(t)$ => both models Mod $7M$, Mod $7M(t)$ => model $7M$ Mod $8M$, Mod $8M(t)$ => model $8M$
	Model $5M(t)$	1.85^{**}	-					
	Model $7M$			-	0.77			
	Model $7M(t)$			-1.78^{*}	-			
	Model $8M$					-	0.77	
	Model $8M(t)$					-1.77^{**}	-	

*** $p \leq 0.001$; ** $p \leq 0.01$; * $p \leq 0.05$.

The outcomes show that accounting for dynamics in the potential market does not yield a better specification when we analyze models “7” and “8”, whereas with model “5” this makes the new specification as good as the previous one.

Figures 5.7 and 5.8 show the diffusion curves of models “5”, “7” and “8” with a fixed potential market and the same models with a dynamic potential market respectively.

Figure 5.7.
Real and estimated values (model 5, model 6 and model 8)
with a fixed potential market

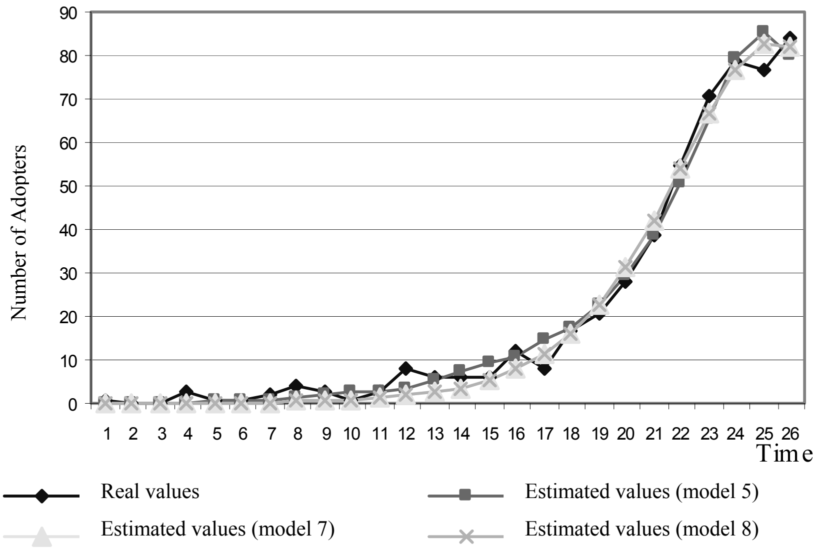


Figure 5.7 starts at t=1

Figure 5.8.
Real and estimated values (model 5 and model 8)
with a dynamic potential market

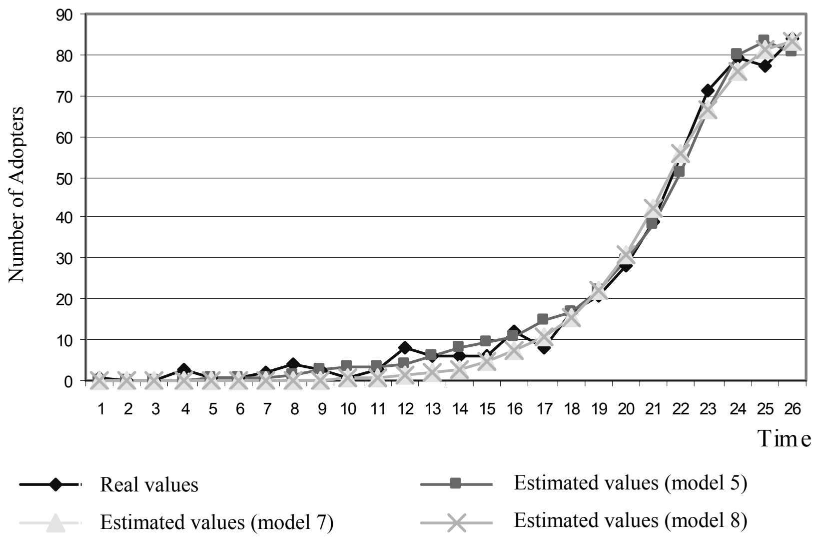


Figure 5.8 starts at t=1

Given the inconclusive results of the Cox test, other criteria are needed to decide which model "5", "7" or "8" is preferred. In the next step, we show the parameter stability and predictive validity of the models to select the most appropriate model among the retained models.

5.6.4. Step 4: Model stability and predictive validity

Our major objective in this study is to propose alternative diffusion models to capture the diffusion process of an organizational innovation, such as franchising, in Spain. In the previous subsections we estimate the proposed diffusion models and show the face validity, the fitting results and some tests to select the most appropriate model. Previous analyses show that there are several models that appropriately describe the diffusion process of franchising in Spain. However, the analysis of each model's performance is completed with an assessment of the parameter stability and the predictive validity of those models that seem to be the most appropriate.

Parameter stability

To evaluate parameter stability we follow Golder and Tellis (1998). We estimate each model repeatedly, starting with a short data series and adding one additional period every time we re-estimate. We use the two measures of parameter stability proposed by the above authors:

- STAB1, which captures fluctuations from the overall mean. This measure is "*the mean of the estimates of the parameter divided by the standard deviation of estimates, where the multiple estimates are obtained by adding an additional year to the data*" (Golder and Tellis (1998, p. 269)):

$$\text{STAB1} = \frac{\text{mean }(\hat{\beta})}{\text{stand.dev. }(\hat{\beta})} \tag{5.19}$$

  where $\hat{\beta}$ represents the parameter estimates.

- STAB2, which captures period to period fluctuations. This measure is "*the average period to period change standardized by the mean of the parameters*" (Golder and Tellis (1998, p. 270)):

$$\text{STAB2} = \Sigma \left| \frac{\hat{\beta}_t - \hat{\beta}_{t-1}}{\text{mean }(\hat{\beta})} \right| \frac{1}{K} \tag{5.20}$$

  where $\hat{\beta}$ represents the parameter estimates and K the number of estimation periods.

Higher STAB1 values indicate that the model presents greater parameter stability, and lower STAB2 values indicate that the model presents greater parameter stability (given that STAB2 captures instability). Table 5.13 shows the values of STAB1 and STAB2 for models "5", "7" and "8" assuming fixed and dynamic potential markets. This table reveals that: i) assuming a fixed potential market yields greater parameter stability than assuming a dynamic potential market (except for STAB1 of $\hat{\beta}_1$ in model "7"), and ii) the parameters of model "7" are more stable than those of models "5" and "8" in both cases (assuming a fixed or dynamic potential market). Therefore, the proposed measures of parameter stability show model "7", with a fixed potential market, as the model with the most stable parameters.

Table 5.13.
Measures of stability of parameters estimates

Fixed potential market -*M*-

	Model 5*M*			Model 7*M*			Model 8*M*	
	$\hat{\beta}_2$	$\hat{\beta}_4$	$\hat{M}$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{M}$	$\hat{\beta}_2$	$\hat{M}$
STAB1	1.15	0.46	0.84	0.55	2.90	1.54	2.70	0.97
STAB2	0.51	1.02	0.72	1.00	0.16	0.48	0.19	0.85

Dynamic potential market -*M*(*t*)-

	Model 5*M*(*t*)			Model 7*M*(*t*)			Model 8*M*(*t*)	
	$\hat{\beta}_2$	$\hat{\beta}_4$	$\hat{\beta}_5$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_5$	$\hat{\beta}_2$	$\hat{\beta}_5$
STAB1	0.86	0.40	0.67	0.61	1.47	0.84	1.45	0.54
STAB2	0.59	1.43	1.46	1.17	0.39	0.74	0.50	1.37

Forecasting ability

To compare the predictive qualities of the selected models we use step-ahead forecasting. We estimate the parameters of models "5", "7" and "8" using the observations of twenty-four periods. We select the twenty-fourth period given that this is the last period before (or around) the peak in the diffusion rate (Bass, Krishnan and Jain, 1994). We do this for models with both fixed and dynamic potential markets. Then, we forecast adoption for the twenty-fifth period. We then re-estimate the models for twenty-five periods and forecast adoption for the twenty-sixth period. Table 5.14 represents the values of the mean absolute percentage error (MAPE) of the selected models. From this table we deduce that model “7”, assuming a fixed potential market, has the lowest MAPE and hence the highest predictive power[17].

Table 5.14.
Predictive accuracy of the model 5, 7 and 8

One-step ahead forecasting results Prediction: 2 periods		
	MAPE (Mean Absolute Percentage Error)	
Model	Fixed potential market -*M*-	Dynamic potential market -*M*(*t*)-
Model 5	35.12	43.99
Model 7	17.88	38.19
Model 8	26.36	38.20

$MAPE = \frac{1}{n^0}\sum_i \left|\frac{y_i - \hat{y}_i}{y_i}\right|$ where n^0 is the number of periods to be predicted.

Among the models that previous analyses show as appropriate models to describe the diffusion process of franchising in Spain (models “5”, “7” and “8”), model “7”, with a fixed potential market (the traditional Bass model), shows better proprieties in terms of parameter stability and predictive validity. Model “7” shows that the adoption process of franchising is governed by both external influence and the influence of adopters (i.e. franchisors) that interact with each other in a contagious process (internal influence). The estimated value of $\hat{\beta}_1$ (=0.00002) is positive, significantly different but close to zero whereas the magnitude of $\hat{\beta}_2$ (=0.39) indicates intensive imitating behavior of Spanish adopting firms. The low relevance of the parameter of external influence, β_1, which represents the innovating behavior of the adopters (franchisors), indicates that there is weak external influence.

[17] Heeler and Hustad (1980) found that the Bass model generally generates better predictions if the time-series data used to calibrate the model includes the peak.

5.7. Conclusions

The literature of diffusion of innovations recommends the application of diffusion models to multiple and different areas in order to contrast how the forces of behavior of the adopters act in different situations. This paper provides insights on how diffusion theory can be applied to a popular organizational innovation, namely franchising. We investigate the diffusion process of franchising as a form of business organization (i.e. inter-firm diffusion). There is no previous research on this focus. Although Nevers (1972) studies the diffusion of franchising, he focuses on how franchisors incorporate new franchise holders (i.e. intra-firm diffusion). In Never's study, the adopters are the franchisees whereas in our study, the adopters are the franchisors. This study contributes to increasing the use of diffusion models in industrial/business settings which, according to Kahn (2002), is very limited. It also contributes to the research on organizational innovations which, according to Van der Aa and Elfring (2002) and Wolfe (1994), is relatively undeveloped.

We perform analyses to find the most appropriate model to describe the diffusion of franchising by Spanish firms between 1974 and 1999. We used four consecutive steps to find this model. Empirical analyses suggest that the long-run diffusion process of franchising in Spain is appropriately captured by several Bass-type diffusion models among a family of models. However, the traditional Bass model presents better properties in terms of parameter stability and predictive validity. Results show that the adoption of franchising in Spain is only marginally influenced by external influence whereas Spanish franchisors present strong imitating behavior. This suggests that if the Spanish Government, Spanish Franchising associations or Spanish Franchising fairs want to stimulate the adoption of franchising among Spanish firms, the external influence should be enhanced by marketing efforts.

Furthermore, the results show the suitability of the imitation hypothesis of the diffusion models to explain the diffusion process of franchising in Spain, which is questioned by Mahajan, Sharma and Bettis (1988) with regard to organizational innovations.

In this study we consider all Spanish firms and do not distinguish between firms in different industries. It is more informative to specify models that describe the adoption of franchising for the different industries. The appropriate data that are necessary to calibrate these models are however, not yet available. This offers opportunities for future research. This also holds true for studies in which the adoption of franchising is analyzed for different countries.

Chapter 6

Diffusion of prescription drugs in the United States of America

6.1. Introduction

The issue of costs and benefits of prescription drug promotion has been the subject of ongoing debate between opponents and proponents of the pharmaceutical industry and has long been a focal point in policy discussions between regulatory agencies and the industry. Pharmaceutical marketing has been criticized as wasteful and excessive and for contributing to the overuse, misuse, and misprescription of drugs (Families USA, 2002). However, marketing may also serve as a key communication channel for continuing physician education regarding pharmaceutical products and for exposing consumers to information that may improve health outcomes (Rubin, 2003).

For the pharmaceutical industry innovations are vital and expenditures on Research and Development are very high. For the industry it is important to discover factors that accelerate adoption of newly developed products so that the likelihood of a profitable R&D investment can be maximized. This is also important from the patient's point of view as health outcomes improve via rapid diffusion of new drugs that provide unique and superior benefits. In this study we focus on estimating the effects of the different marketing instruments on the diffusion process of new prescription drugs, and also on the analysis of separate effects of marketing directed at physicians ("push" strategy) and direct-to-consumer advertising ("pull" strategy).

We use a trial-repeat purchase diffusion model that we calibrate for each drug in the category of rhinitis drugs. This category contains only branded products, most of which are introduced during the observational period (1993-2000). We also calibrate the model using data of two other categories: osteoarthritis-rheumatoid-arthritis and asthma. The rhinitis and the asthma categories are quite similar (they both treat the respiratory organs and display seasonal patterns), whereas the osteoarthritis-rheumatoid-arthritis category is completely different from the other two. The osteoarthritis-rheumatoid-arthritis category and the asthma category are much older than the rhinitis category. Hence, in contrast to the rhinitis category, these do not only contain branded products but also generics.

The trial-repeat purchase diffusion model that we develop is an extension of the model of Hahn et al. (1994). We propose to incorporate the effect of company and competitors' promotional efforts separately. In contrast to other studies that either use aggregate measures for marketing expenditures or expenditures for a single instrument (Lilien, Rao and Kalish 1981, Rao and Yamada 1988, Hahn et al., 1994), our model accommodates heterogeneity in the effects of different marketing instruments. Following existing literature, we assume that the trial rate is time varying and that it depends on marketing expenditures.

However, unlike previous research on trial-repeat diffusion models that assume *a priori* that marketing instruments affect the trial rate through the external influence, we first analyze a family of diffusion models that allows us to detect the appropriate allocation for marketing instruments in the trial rate. We hypothesize that longitudinal relationships exist both for own-brand and competitors' marketing efforts.

We also accommodate so-called cross-sectional effects: we investigate how marketing expenditures affect the basic propensity to try a new product, internal influence and the repeat rate. We investigate these effects by performing a second-stage analysis on the results of the diffusion model, which are obtained separately for multiple brands.

In summary, our contributions are:

- we investigate both longitudinal and cross-sectional effects of marketing expenditures on the diffusion of pharmaceutical products;
- our model accommodates heterogeneity in the effects of the different marketing instruments;
- we do not make *a priori* assumptions about how the allocation of marketing instruments affects the diffusion process. We determine empirically whether the marketing instruments influence the diffusion process through the trial rate (through the internal and/or external influence) or through the repeat rate;
- our model specification accommodates the effects of both own and competitors' marketing expenditures on the diffusion process;
- we separately determine the effect of marketing expenditures on the trial rate ("informative" function) and on the repeat rate ("persuasive" function);
- our results show that the diffusion process is clearly affected by marketing directed at physicians and slightly affected by direct-to-consumer advertising;
- our results provide support for the existence of both longitudinal and cross-

sectional diffusion effects in the market of three drug categories: rhinitis, osteoarthritis-rheumatoid-arthritis and asthma.

The results of this study allow us to perform an in-depth analysis of the impact of the different marketing instruments on the time-varying diffusion parameters. We use a recursive time window approach and show preliminary results. These results suggest that marketing directed at physicians, especially detailing and then physician meetings, affect the longitudinal pattern of the diffusion parameters.

The rest of this chapter is set up as follows. In Section 6.2 we focus on the importance of marketing in the pharmaceutical industry, especially for new products, and the buying decision process in this industry. In Section 6.3 we provide a brief literature review of research addressing diffusion models for non-durable products that accounts for repeat purchases and that analyzes the impact of marketing variables on the diffusion process. We also review existing trial-repeat diffusion models validated on pharmaceutical products. In Section 6.4 we specify our diffusion model. In Sections 6.5 and 6.6 we present the data and the estimation results, respectively. Finally, we discuss our conclusions in Section 6.7.

6.2. The Pharmaceutical Industry

In this section we discuss the main characteristics of the pharmaceutical industry, we point out the relevance of pharma marketing and explain the particular buying decision process in this industry.

The pharmaceutical industry has been the most profitable industry in the USA, as measured by median return on revenue, for each of the 10 years before 2002 (Families USA, 2002). In Table 6.1 we show that the top 9 pharmaceutical companies spend on average 11 percent ($19 billion) of total revenue on R&D. The US General Accounting Office (a research bureau of the US Congress) reports that the US Pharmaceutical firms spent $30.3 billion on R&D in 2001 (US General Accounting Office, 2002). The competitive advantage of a new pharmaceutical product is a temporary impact due to patent expiration. Hence, it is of interest to determine factors that accelerate the diffusion process, for example to recover the R&D costs more quickly. We focus on marketing as a possible means for increasing the speed of diffusion. According to Families USA (2002), "*The drug industry pumps huge sums of money into marketing because it works. Advertising and marketing help drive sales, and top-selling drugs can generate large revenues*" (p.13). Leffler (1981, p.52) points out that "*prescription drugs are one of the most heavily promoted products in the American economy*". In the US, the marketing expenditures are somewhere between $10 and 20 billion annually (see, e.g. Breitstein, 2002). Pharma marketing expenditures[1] potentially help the pharmaceutical industry to quickly recover the R&D costs by providing useful and beneficial information to physicians and patients. "*This is the role of marketing – providing information to decision makers*" (Rubin, 2003, p.7). Another possible effect of marketing activities is that they might create effective barriers for new entrants so that market shares are protected.

Table 6.1.
2001 Financials for U.S. Corporations Marketing the Top 50 Drugs for Seniors

Company	Revenue (Net Sales in Millions of Dollars)	Percent of Revenue Allocated to:		
		Marketing/ Advertising/ Administration	R & D	Profit (Net Income)
Merck & Co., Inc.	$47,716	13%	5%	15%
Pfizer, Inc.	$32,259	35%	15%	24%
Bristol-Myers Squibb Company	$19,423	27%	12%	27%
Abbott Laboratories	$16,285	23%	10%	10%
Wyeth	$14,129	37%	13%	16%
Pharmacia Corporation	$13,837	44%	16%	11%
Eli Lilly & Co.	$11,543	30%	19%	24%
Schering-Plough Corporation	$9,802	36%	13%	20%
Allergan, Inc.	$1,685	42%	15%	13%
Total* (Dollars in millions)	**$166,678**	**27%** $45,413	**11%** $19,076	**18%** $30,599

* Totals may not add due to rounding.

Source: Families USA (2002)

The instruments of pharmaceutical marketing

When considering the strategic issues facing medical marketers in the pharmaceutical industry we distinguish "push" and "pull" strategies. The pharmaceutical industry has traditionally used a "push" strategy focusing their promotional budget directly on the physicians. The most important promotional

[1] See Rubin (2003) for a detailed explanation of the allocation of pharma marketing expenditures.

instruments that are used with this strategy are detailing, physician meetings and seminars, medical journal advertising, samples and direct mail. Detailing is the name of the promotional activity that consists of sales representatives (detailers) visiting physicians in order to provide information on e.g. appropriate drug usage (efficacy, indications, contra-indications, side effects, etc.), modes of therapy, prices, etc. Physician meetings and seminars involve talks that are organized or sponsored by pharmaceutical companies where experts discuss the treatment of specific diseases or illnesses. Medical journal advertising refers to advertisements for specific pharmaceuticals in medical journals. Samples refer to the free product samples distributed by pharmaceutical firms. Direct mail includes the printed material sent out to physicians as information aids. Among the previous promotional activities, detailing has been and continues to be the primary form of promotion directed at physicians.

Another strategy is to use direct-to-consumer advertising (i.e. promotional activities used by pharmaceutical firms directed at consumer). Direct-to-consumer advertising can be classified as a "pull" strategy. Consumers tend to have positive attitudes toward direct-to-consumer ads. Handlin, Mosca, Forgione and Pitta (2003) show that approximately 10 million people requested an advertised drug from their doctor in 1997. These positive attitudes towards direct-to-consumer advertisements are relevant given that they might lead patients to increase compliance. Due to direct-to-consumer advertising patients are more educated in terms of what types of drugs and treatments are available to them (Butler, 2002). Direct-to-consumer advertising can make someone aware that he or she may have a treatable condition, for example through an advertisement explaining the symptoms of depression (Rubin, 2003). Direct-to-consumer advertising is gaining a relevant place in pharma marketing, particularly in the USA, one of the few countries where direct-to-consumer advertising is allowed. In the USA, direct-to-consumer advertising used to be heavily restricted until 1997, when the Food and Drug Administration (FDA) changed its ruling and relaxed their restrictions significantly.

Parker and Pettijohn (2003) report that direct-to-consumer advertising costs increased from approximately \$40 million in 1989 to \$160 million in 1994 and to 350\$ million by 1995. By 1996 the expenditures on direct-to-consumer advertising was estimated to have doubled to approximately \$700 million. The US General Accounting Office shows that expenditures on direct-to-consumer advertising increased by 145 percent between 1997 and 2001. In 1997, direct-to-consumer advertising accounted for 10 percent of total spending on promotion, whereas in 2001 it accounted for almost 14 percent (\$2.7 billion dollars, see US General Accounting Office, 2002). Recent research shows that promotional expenditures on direct-to-consumer advertising are concentrated on a small number of medications and that promotions directed to physicians remain dominant, but that direct-to-consumer advertising has become key for a subset of medications (Ma, Stafford, Cockburn and Finkelstein, 2003). Wittink (2002), in a study of 392 branded drugs, reports that the firms under study invested approximately 8.5 billion dollars on direct-to-physician marketing in 2000 and 2.5 billion on direct-to-consumer advertising.

Pharmaceutical firms use both promotion directed at physicians and direct-to-consumer advertising to inform the market about their products. The use of both strategies has important implications, given that with the "pull" strategy the patients could play a role in the decision what drug is prescribed. However, existing research (Rosenthal, Berndt, Donohue, Frank and Epstein, 2002; Wosinska, 2002; Xie, 2003) reveals that although direct-to-consumer advertising allows patients to be better informed about their health conditions, this does not affect the physician's decision.

The role of pharma marketing on the trial rate (external and internal influences)

Pharma marketing activity can influence the trial rate of the new prescription drugs. In the trial rate of new drugs we differentiate to types of influences: external and internal influence (see Chapter 2). External influence is related to the innovative behavior of physicians, which can be modified by promotional activities developed by firms. Marketing activities of pharmaceutical products may allow for better health care and lower costs as it helps physicians to keep up-to-date with medical treatments, therapies and medications (Mossinghoff, 1992). Internal influence is related to the interpersonal communication among physicians about the new drugs introduced into the market; i.e. the influence resulting from interaction between previous and potential adopters of the new drugs. The more widely a drug is used, the more we can expect this drug to be effective and safe. For example, physicians may assume that the probability of a malpractice suit is lower for an existing brand than for a new drug. Temin (1980) suggest that since physicians do not have access to well-organized data that allow them to make comparisons about the efficacy and risk of substitute drugs, their decisions about drugs are based on the customary behavior of other physicians (Berndt, Pindyck and Azoulay, 2003). Pharma marketing can improve this situation by offering useful information on new pharmaceutical products. Hence, pharma marketing can affect physician's behavior through both types of influences and play a relevant role in the physician's decision to prescribe a new drug.

The role of pharma marketing on the repeat rate

Prescription drugs belong to the category of frequently purchased products where adopters may switch from one product to another substitute product in the short term. Therefore, the role of pharma marketing activities is also very relevant here as these activities may influence a physician's decision to prescribe the same (new) drug instead of a substitute drug. Pharma marketing may help to a physician that his/her initial choice is the most appropriate for patients' health outcomes, and in that manner reduce the probability of a switch to a competing drug.

Pharma marketing: information or persuasion?

The literature distinguishes two functions for pharma marketing activities: an "informative" and a "persuasive" function (Leffler, 1981; Hurwitz and Caves, 1988; Rizzo, 1999). It is of interest for managers to know their role on the diffusion processes of new pharmaceutical products.

When there are several competing products available to treat a certain disease, a physician may have selected a "preferred product", possibly based on efficacy considerations, severity of side effects, etc[2]. With the introduction of a new alternative the physician may reconsider his/her choice of a preferred drug. The outcome of this reconsideration may be influenced by the amount of information that is provided by the manufacturers of the new product. That is, marketing activities allow physicians to update their prior beliefs about the new product. Hence, pharmaceutical marketing may influence the diffusion process of a new product through the trial rate. This is what some authors call the "informative" function of marketing activities. The role marketing plays in providing information about new treatments and drugs is crucial to health care. This is especially important in the pharmaceutical industry where developing successful new products is of vital importance. If physicians and patients do not have sufficient information about how and why to use a new drug, their interest in the new drug will be low whatever the price. In the USA pharmaceutical industry, which spent over $20 billion promoting and marketing their products in 2002, pharma marketing is the main source of information on new cures, treatments and medications (Manning and Masia, 2003). As pointed out by Rubin (2003, p.12) "*The absence of information would severely restrict access to innovative products. Note that the spread of new medicines has been shown to reduce other types of health care spending such as hospitalization, implying that without information on new medicines, overall health spending might increase*".

The "persuasive" function of pharma marketing refers to the influence that marketing activities have in creating market power for the promoted product. In this sense, the "persuasive" function of pharma marketing builds barriers of entry to competitors into the marketplace. Hurwitz and Caves (1988) find that marketing activities protect the market share of innovators when generics enter the market.

[2] We note that part of this selection procedure may also be performed by health maintenance organizations -HMOs- or insurance companies that select preferred products based on benefit/cost considerations. These preferences show up in formularies (drugs for which the HMO provides full or partial coverage in the form of reimbursements).

Hence, this "persuasive" function influences the diffusion process of a new product through the repeat rate.

Other authors distinguish between the indirect ("informative") and direct ("persuasive") effects of pharma marketing communication. The studies of Erdem and Keane (1996) on laundry detergents, Currie and Park (2002) on prescription of antidepressants, and Ackerberg (2003) on yogurt have found evidence only for the indirect effect ("informative" function) of marketing communication; others like those of Anand and Shachar (2001) on Television shows and Narayanan, Manchanda and Chintagunta (2004) on prescription of antihistamines have found evidence for both the indirect ("informative") and direct ("persuasive") effects[3]. Hence, there is evidence for both the "informative" and "persuasive" function of pharma marketing communication.

The buying process of pharmaceuticals

In the remainder of this section we focus on the buying decision process in the pharmaceutical industry. In this industry we distinguish two processes depending on the kind of drug considered: the buying decision process in the over-the-counter (OTC) drug market and the buying decision process in the prescription drug market.

The OTC drug market shows the traditional process where the decision maker is also the end-user of the product (Akçura, Gönül and Petrova, 2004). However, in the prescription drug market, the users are not the decision makers. The users, patients, may influence the decision-making process but the physicians prescribe the (prescription) drugs after which patients purchase the drugs. Hence, although the consumers are the users, they are not the decision makers. The decision to choose a specific drug can be influenced by both patients and physicians, but the ultimate decision is made by the physician.

Another important difference between the OTC and prescription drug markets that affects the buying decision process is related to price. Intermediaries such as insurance firms, health maintenance organizations -HMOs- or government agencies pay for more of the cost of the prescription drugs. Hence, one might expect that insured patients have little awareness of the full price, and hence will not be very sensitive to it. In the United States about 87 percent of the population -approximately 221 million adults between the ages of 18 and 64- have some kind of health care insurance (Narayanan, Manchanda and Chintagunta, 2004) that includes coverage of prescription drugs. The physicians, working in the interest of the patient, have no financial stimulus either to be price sensitive and they tend to be ignorant of the full price of specific drugs (Hurwitz and Caves, 1988). Newhouse (1993) finds no evidence that physicians prescribe lower-price drugs to

[3] For more details see Narayanan, Manchanda and Chintagunta (2004).

patients who have less generous insurance coverage. Hellerstein (1998) does report that physicians are somewhat price sensitive for prescription drugs when generics compete with branded drugs. Her study reports evidence that physicians are more likely to prescribe generic than branded drugs when they have a relative large number of patients covered by insurance plans. Real competition in the pharmaceutical industry comes when generics enter the marketplace; generic drugs are about half the full price of branded drugs in the first year after a generic is introduced in the market (Families USA, 2002). Gönül, Carter, Petrova and Srinivasan (2001) find evidence that considerations about drug efficacy and patients' conditions are the primary drivers in the decision process, overriding price concerns. In general, price is a factor of little concern to physicians and patients in the case of health insurance coverage.

6.3. Literature review

The literature on the diffusion of new products reveals the wide acceptance of the Bass model (Mahajan, Muller and Wind, 2000). However, this model is built on assumptions that reduce its applicability (see Chapter 2, Section 2.4), but at the same time invite researchers to extend the model. We focus on two of these assumptions that make the Bass model less appropriate for analyzing diffusion processes of new drugs. The Bass model assumes that each adopter purchases the new product only once (see Chapter 2, Section 2.4.2.4). This assumption reduces the applicability of the model to durables (without a replacement option), and makes it less suitable for non-durables that involve repeated purchases. Another restrictive assumption of the Bass model is that the impact of the marketing variables is implicitly captured by the model parameters (see Chapter 2, Section 2.4.2.9). This assumption makes it impossible to analyze the effect of marketing instruments on the diffusion process of the innovation. In the pharmaceutical industry where firms invest a huge amount of dollars in marketing, the analysis of the effects of pharma marketing is an essential issue to managers.

Several authors like Dodson and Muller (1978), Dolan and Jeuland (1981), Lilien, Rao and Kalish (1981), Jeuland and Dolan (1982), Mahajan, Wind and Sharma (1983), Parker and Gatignon (1994) and Hahn et al. (1994) modified the Bass model to allow for non-durable products and repeat purchases. Several of these applications deal with pharmaceutical products. In this respect Lilien, Rao and Kalish (1981) and Hahn et al. (1994) propose trial-repeat diffusion models with promotional efforts. Rao and Yamada (1988) validate the work of Lilien, Rao and Kalish (1981) on twenty products. Mahajan, Wind and Sharma (1983) focus on the non-uniform nature of the internal influence.

The incorporation of marketing mix variables into diffusion models is important because by measuring the effects of marketing on the diffusion process, marketing strategies for new products may be improved (Mahajan and Muller, 1979; Kalish and Sen, 1986; Mahajan and Wind, 1986; Mahajan, Muller and Bass, 1990; Bass, Jain and Krishnan, 2000). Given the evident importance of marketing variables on the diffusion process of innovations, many authors have proposed diffusion models that incorporate marketing variables and have provided empirical support (see Chapter 2, Section 2.4.2.9). Most of these studies focus on durable products, and the empirical evidence is not conclusive. Concerning the effect of advertising on diffusion rate: Horsky and Simon (1983) and Simon and Sebastian (1987) find that advertising affects the diffusion rate of banking telephoning and telephones, respectively. Horsky and Simon (1983) investigate only one possibility: advertising affects the diffusion rate through the external influence. However, Simon and Sebastian (1987) consider that advertising can affect external and/or internal influence; their results show that, although advertising efforts affect both external and internal influence, the model that considers that advertising only affects the internal influence is slightly superior. Bass, Krishnan and Jain (1994) introduce advertising into the Bass model by assuming separable[4] effects for advertising (i.e. advertising affects both external and internal influence) and find a positive advertising influence on the diffusion rate of high priced durable products. Mesak (1996) considers different options to include advertising: separable and non-separable effects (i.e. advertising impact on the parameter of external influence or the parameter of internal influence); he concludes that advertising affects the diffusion rate through both external and internal influence. Although the empirical findings of these authors are not conclusive, they agree on the positive sign of advertising influence.

Unfortunately, little is known about the effects of the marketing instruments on the diffusion process of frequently purchased products. We have found the empirical work by Parker and Gatignon (1994) on five brands of hair styling mousse, and applications by Lilien, Rao and Kalish (1981), Rao and Yamada (1988) and Hahn et al. (1994) on prescription drugs. In this section we first make some general remarks on these articles and then discuss the last three articles in greater detail.

Parker and Gatignon (1994) study frequently purchased products, but only consider first purchases (trials). They analyze both separable effects and non-separable effects for advertising, and find that advertising affects the trial rate with the expected signs in three out of five brands analyzed. However their results are not conclusive on how to include the effect of marketing in a diffusion model: a different model is selected for each of these three brands. For one brand the

[4] Separable effects and non-separable effects are discussed in Section 2.4.2.9.

preferred model is the one that accommodates the external influence of advertising, for another brand the model that allows for the internal influence is preferred, and for the third the model in which advertising affects both internal and external influence is selected. In the other three papers, the authors consider both first and repeat purchases and, hence, unlike Parker and Gatignon (1994), assume that diffusion rate is divided into a trial rate and a repeat rate. Lilien, Rao and Kalish (1981) find positive and significant, although small, effects of detailing expenditures and the squared company's detailing expenditures on sales. The opposite holds for the competitive detailing effects. Their results also demonstrate that the company's detailing expenditures increase the trial rate through the external influence whereas the competitors' detailing expenditures decrease the repeat rate. The findings of Lilien, Rao and Kalish are supported by Rao and Yamada (1988). Hahn et al. (1994) analyze twenty-one prescription drugs and consider the effects of detailing and medical journal advertising (considering them as an aggregated marketing instrument). They find positive and significant effects for the company's marketing efforts on the trial rate through the external influence.

We now discuss in greater detail the trial-repeat diffusion models developed by
a) Lilien, Rao and Kalish (1981), we refer to this model as the LRK model;
b) Mahajan, Wind and Sharma (1983), the MWS model, and
c) Hahn, Park, Krishnamurthi and Zoltners (1994), the HPKZ model.

a) The LRK model

Lilien, Rao and Kalish (1981) develop a model for the early forecasting of prescription drug sales. Specifically, they propose[5]:

$$\begin{aligned} s_{i,t} = & \left(\beta_{11i} x_{i,t-1} + \beta_{12i} x_{i,t-1}^2\right)\left[m - s_{i,t-1}\right] \\ & + \beta_{2i}\left(s_{i,t-1} - s_{i,t-2}\right)\left[m - s_{i,t-1}\right] + \left(1 - \beta_{3i} x_{c,t-1}\right) s_{i,t-1} \end{aligned} \tag{6.1}$$

where, for brand i ($i = 1, \ldots, N$) in month t ($t = 1, \ldots, T$):

$s_{i,t}$ = sales of brand i in time period t;
$x_{i,t}$ = detailing effort associated with brand i in time period t;
$x_{c,t}$ = detailing effort associated with the competing brands in time period t;
m = total market sales;
β_{11i}, β_{12i}, β_{2i}, β_{3i} = parameters to be estimated.

[5] To facilitate comparison among the described models, we use the same terminology.

The LRK-model consists of three components:

(1) $\left(\beta_{11i}x_{i,t-1} + \beta_{12i}x_{i,t-1}^2\right)\left[m - s_{i,t-1}\right]$

(2) $\beta_{2i}\left(s_{i,t-1} - s_{i,t-2}\right)\left[m - s_{i,t-1}\right]$

(3) $\left(1 - \beta_{3i}x_{c,t-1}\right)s_{i,t-1}$.

Term (1) represents triers of brand *i* due to the company's promotional efforts, term (2) triers of brand *i* due to the internal influence and term (3) repeaters of brand *i* as an expression that accounts for the competitors' promotional efforts. Although the LRK-model is developed to describe and analyze the physician's prescription behavior, the estimation is done on the brand sales level. The LRK-model includes the effects of the company's and the competitors' promotional efforts and the internal influence. Although the authors have available data about medical journal advertising, direct mail and detailing expenditures, they only consider the effect of detailing expenditures given the high correlation between the promotional activities.

b) The MWS model

Mahajan, Wind and Sharma (1983) extend the first-purchase non-uniform influence model proposed by Easingwood, Mahajan and Muller (1983) by proposing a repeat-purchase diffusion model -the MWS-model- which specifically considers the non-uniform nature of the internal influence:

$$s_{i,t} = \beta_{1i}\left[m - s_{i,t-1}\right] + \beta_{21i}\left(\frac{s_{i,t-1}}{m}\right)^{\beta_{22i}}\left[m - s_{i,t-1}\right] + \beta_{3i}s_{i,t-1} \tag{6.2}$$

where, for brand i (i = 1, … , N) in month t (t = 1, …, T):

$s_{i,t}$ = sales of brand i in time period t;

m = total market sales;

$\beta_{1i}, \beta_{21i}, \beta_{22i}, \beta_{3i}$ = parameters to be estimated.

In the MWS-model we distinguish three components:

(1) $\beta_{1i}\left[m - s_{i,t-1}\right]$

(2) $\beta_{21i}\left(\frac{s_{i,t-1}}{m}\right)^{\beta_{22i}}\left[m - s_{i,t-1}\right]$

(3) $\beta_{3i}s_{i,t-1}$.

Term (1) represents the sales effects of brand *i* due to triers that are affected by external influence (company's promotional efforts among others), term (2) is the sales effect of brand *i* that results from internal influence (such as word-of-mouth communication) and term (3) represents the sales effect due to repeat purchases of repeaters of brand *i*. Term (2), the internal influence, represents the time-varying effect of imitation. The parameter β_{22i} is the non-uniform influence parameter ($\beta_{22i} \geq 0$). This term allows the internal influence effect to increase, decrease and remain constant over the penetration horizon. The incorporation of the non-uniform nature of the internal influence (see also Chapter 2, Section 2.4.2.3, and Chapter 5) makes the model more realistic.

c) The HPKZ model

Hahn et al. (1994) extend the diffusion framework of previous studies and develop a four-segment (triers, non-triers, repeaters and non-repeaters) trial and repeat model -the HPKZ-model- that can be calibrated using aggregate data for frequently purchased products in the early stages of the product life cycle. The HPKZ-model offers the opportunity to estimate the long run average market share of the new product. The HPKZ-model accommodates, although in a different way to the LRK-model, the effect of the internal influence and the company's promotional efforts. The authors specify two versions of the HPKZ-model. In the first version, HPKZ1, promotional spending enters the model as a relative variable. In the second version, HPKZ2, promotional spending is not divided by the total promotional spending:

HPKZ1

$$s_{i,t} = \left(\beta_{11i} + \beta_{12i} \ln\left(\frac{x_{i,t-1}}{x_{i,t-1} + x_{c,t-1}}\right)\right)\left[m - q_{i,t-1}\right] + \beta_{2i}\left(\frac{s_{i,t-1}}{m}\right)\left[m - q_{i,t-1}\right] + \beta_{3i} q_{i,t-1} \tag{6.3}$$

HPKZ2

$$s_{i,t} = \left(\beta_{11i} + \beta_{12i} \ln\left(x_{i,t-1}\right)\right)\left[m - q_{i,t-1}\right] + \beta_{2i}\left(\frac{s_{i,t-1}}{m}\right)\left[m - q_{i,t-1}\right] + \beta_{3i} q_{i,t-1} \tag{6.4}$$

with $q_{i,t} - q_{i,t-1} = s_{i,t} - \beta_{3i} q_{i,t-1}$,

where, for brand i ($i = 1, \ldots, N$) in month t ($t = 1, \ldots, T$):

$s_{i,t}$ = sales of brand i in time period t;
$x_{i,t}$ = detailing and advertising efforts associated with brand i in time period t;
$x_{c,t}$ = detailing and advertising efforts associated with the competing brands in time period t;
m = total market sales;
$q_{i,t-1}$ = potential sales of brand i to physicians in the post-trial segments (triers, repeaters and buyers of competing brands that have tried brand i before) at time t-1;
β_{11i}, β_{12i}, β_{2i}, β_{3i} = parameters to be estimated.

As in the previous models, we identify three components in the HPKZ-model:

(1) $\left(\beta_{11i} + \beta_{12i} \ln\left(\frac{x_{i,t-1}}{x_{i,t-1} + x_{c,t-1}}\right)\right)\left[m - q_{i,t-1}\right]$ in version HPKZ1

$\left(\beta_{11i} + \beta_{12i} \ln\left(x_{i,t-1}\right)\right)\left[m - q_{i,t-1}\right]$ in version HPKZ2

(2) $\beta_{2i}\left(\frac{s_{i,t-1}}{m}\right)\left[m - q_{i,t-1}\right]$

(3) $\beta_{3i} q_{i,t-1}$.

Term (1) represents triers of brand i due to the external influence (which is influenced by the company's and competitors' promotional efforts in version HPKZ1 and only by the company's promotional efforts in version HPKZ2), term (2) represents triers of brand i due to the internal influence and term (3) repeaters of brand i. One interpretation of parameter β_{3i} is that "*it represents the long run average market share of the new product because the total market is represented by the repeat market after the trial market is saturated*" (Hahn et al., 1994, p.229). Among the trial-repeat diffusion models, the HPKZ-model has the best fit and forecast ability, and has superior parameter face validity (Hahn et al., 1994). We use this model as the starting point of the development of our model.

6.4. Model specification

In this study, we modify the model of Hahn et al. (1994) to allow for heterogeneity in the effects of the different marketing variables and for differences in the effects of own and competitor's marketing efforts. Previous trial-repeat diffusion models (Lilien, Rao and Kalish, 1981; Hahn et al., 1994) employ a single or aggregated variable to model the effects of marketing instruments on the diffusion process. This aggregation implies that important information is lost about how different types of marketing variables have unique effects. In contrast to previous studies, we consider two promotional strategies: the traditional "push" strategy (medical journal advertising, detailing and physician meetings expenditures) and the "pull" strategy (direct-to-consumer advertising). We extend the HPKZ-model (version HPKZ2) to investigate longitudinal and cross-sectional effects of marketing expenditures on the diffusion of pharmaceuticals. Following the diffusion framework (see also Chapter 2, Section 2.3.1) presented by Hahn et al. (1994), the market is divided into four segments of physicians:

1) non-triers, physicians that are potential prescribers and have never tried the new product;
2) triers, physicians that prescribe the new product for the first time in time period *t*;
3) repeaters, physicians that prescribe the new product earlier and continue prescribing it in time period *t*; and
4) non-repeaters, physicians that have tried the new product in the past, but decided not to prescribe it in time period *t*.

Our model incorporates three characteristics of new product buying behavior: the innovative trial, the imitative trial, and the repeat buying. The innovative and imitative buying behaviors are modeled following Bass diffusion model (see Chapter 2). In a first stage of the diffusion process, the new product is discovered and adopted by a small group of innovative consumers (innovators) who influence others (imitators). This social interaction between the previous adopters and the potential adopters helps to explain the phase of rapid expansion in the diffusion process of innovations (Rogers, 1962, 1995). Hence, we face two kinds of behavior among those who adopt an innovation:

1) innovative behavior, which involves the adopters' basic tendency to innovate (or the adopters' innate innovativeness). This behavior is influenced by sources of external communication;
2) imitating behavior, which involves the tendency to adopt an innovation on the bases of interpersonal influence processes (word-of-mouth or internal communication).

The behavioral theory behind the traditional diffusion models suggests that a time-lag exists between the adoptions by members of a social system and that these adoptions are influenced by experience. Thus, the rate of trial purchases at time *t* is proportional to: i) the size of the market yet to be penetrated and ii) a linear function of previous penetration.

Since we are concerned with the longitudinal effects of both own and competitor's expenditures on the different marketing instruments and also with differentiating between marketing directed at physicians -"push" effect- and direct-to-consumer advertising -"pull" effect-, we propose the following model, which is an extended version of the HPKZ-model:

$$s_{i,t} = \left[\beta_{10i} + \sum_{j=1}^{4} \beta_{1ji} \ln\left(x_{ij,t}\right) + \sum_{j=1}^{4} \beta_{1jci} \ln\left(x_{cj,t}\right) + \beta_{2i}\left[\frac{s_{i,t-1}}{m_t}\right]\right]\left[m_t - q_{i,t-1}\right] + \beta_{3i} q_{i,t-1} \qquad (6.5)$$

with $q_{i,t} - q_{i,t-1} = s_{i,t} - \beta_{3i} q_{i,t-1}$, where, for brand i ($i = 1, \ldots , N$) in month t ($t = 1, \ldots, T$):

$s_{i,t}$ = sales of brand i in time period t (sales from trial and from repeat purchases);

$x_{ij,t}$ = own marketing expenditures on instrument j ($j = 1$: direct-to-consumer advertising; $j = 2$: detailing; $j = 3$: medical journal advertising; $j = 4$: physician meetings) in time period t;

$x_{cj,t}$ = competitors' marketing expenditures on instrument j in time period t;

m_t = total market sales in time period t;

$q_{i,t\text{-}1}$ = potential sales of brand i to physicians in the post-trial segments (triers, repeaters and buyers of competing brands that have tried brand i before) at time t-1;

β_{10i}, β_{1ji}, β_{1jci}, β_{2i}, β_{3i} = parameters to be estimated.

In this model, $s_{i,t\text{-}1} /m_t$ is included to measure the internal influence effects: we assume that the prescribers of brand i at time t-1 are likely to influence non-prescribers to try this brand in time period t. The variable $q_{i,t\text{-}1}$ is included to measure the repeat rate. The parameters in the model can be interpreted as follows. The parameter β_{10i} indicates the basic propensity to try brand i without the influence of prior buyers or marketing expenditures. The effect of own (competitors') promotional activities on the trial rate of brand i is captured by β_{1ji} (β_{1jci}). The parameter β_{2i} captures the effect of internal influence on the trial rate, and β_{3i} is the repeat rate[6]. The proposed model has three components:

$$(1)\ \left(\beta_{10i} + \sum_{j=1}^{4} \beta_{1ji} \ln\left(x_{ij,t}\right) + \sum_{j=1}^{4} \beta_{1jci} \ln\left(x_{cj,t}\right)\right)\left[m_t - q_{i,t-1}\right]$$

$$(2)\ \beta_{2i}\left[\frac{s_{i,t-1}}{m_t}\right]\left[m_t - q_{i,t-1}\right]$$

$$(3)\ \beta_{3i} q_{i,t-1}.$$

Term (1) represents triers of brand i due to external influence, which is determined by the basic propensity to buy at a given period and by own and cross marketing expenditures. Term (2) refers triers of brand i due to internal influence as a result of internal influence. Term (3) represents to the repeaters of brand i.

Equation (6.5) assumes that marketing expenditures affect the diffusion process through the trial rate and more specifically through the external influence (i.e. assuming non-separable effects for marketing expenditures). However, extant literature is inconclusive on how to include marketing instruments in a diffusion

[6] The model represented by Equation (6.5) is expressed in terms of sales, which are directly observable from aggregate data. However, when the model is expressed in terms of consumers (i.e. physicians), it is easy to see that $\hat{\beta}_{3i}$ is a repeat rate, the fraction of post-trial buyers who repurchase brand i in time period t. (see Hahn et al., 1994, pp. 227-228).

model (see also Section 6.2). For that reason, we do not assume *a priori* whether marketing expenditures affect external and/or internal influence. A formulation analogous to Equation (6.5) that accommodates internal influence is presented in Equation (6.6), and a model that allows for both internal and external influence is given in Equation (6.7.):

$$s_{i,t} = \left[\beta_{10i} + \left(\beta_{2i} + \sum_{j=1}^{4} \beta_{2ji} \ln\left(x_{ij,t}\right) + \sum_{j=1}^{4} \beta_{2jci} \ln\left(x_{cj,t}\right) \right) \left[\frac{s_{i,t-1}}{m_t} \right] \right] \left[m_t - q_{i,t-1} \right] \quad (6.6)$$

$$+ \beta_{3i} q_{i,t-1}$$

with $q_{i,t} - q_{i,t-1} = s_{i,t} - \beta_{3i} q_{i,t-1}$,

$$s_{i,t} = \left[\beta_{10i} + \beta_{2i} \left[\frac{s_{i,t-1}}{m_t} \right] \right] \left(1 + \sum_{j=1}^{4} \beta_{4ji} \ln\left(x_{ij,t}\right) + \sum_{j=1}^{4} \beta_{4jci} \ln\left(x_{cj,t}\right) \right) \left[m_t - q_{i,t-1} \right] \quad (6.7)$$

$$+ \beta_{3i} q_{i,t-1}$$

with $q_{i,t} - q_{i,t-1} = s_{i,t} - \beta_{3i} q_{i,t-1}$.

Our model -in all of its formulations: Equations (6.5), (6.6) or (6.7)- has two important limitations.

Firstly, the formulations assume that marketing affects the trial rate but not the repeat rate. Although theoretically both options are possible, we do not consider the influence of marketing on the repeat rate using the same argument as Hahn et al. (1994): "*… the direct experience coming from product trial should be more influential in the repeat market than indirect experience"* (see also Smith and Swinyard, 1982).

Secondly, none of the formulations incorporate price. There are some reasons that have led us to take this decision. Firstly, we have the arguments shown in Section 6.2 that can be synthesized in the following sentence "*Physicians are typically more concerned about product quality and side-effects than they are about price. Thus, price tends to be less important for the diffusion of a new prescription drug. However, it can have an impact on new product diffusion of more price sensitive pharmaceutical products or other product categories*" (Hahn et al., 1994, p. 246). Secondly, price is a very difficult concept to define in the pharmaceutical industry. Although manufacturers determine drugs' prices (list prices), different patients can pay different prices for the same prescription drug, depending on the health plans that they have with HMOs or insurance companies. These companies can negotiate discounts from pharmacies (retailers) or from manufacturers (rebates), and patients with health plans pay co-payments or only a part of the price. Hence, it is difficult to specify a "unique" price concept to incorporate into our model.

We estimate thirteen versions of our model. The versions differ with respect to the three formulations of the model (external influence formulation, see Equation (6.5), internal influence formulation, see Equation (6.6), and both external and internal influence formulation, see Equation (6.7)) and restrictions that we apply to these models. We now discuss the different versions.

- Model version 1: for this version we employ the following restrictions:
$\beta_{11i} = \beta_{12i} = \beta_{13i} = \beta_{14i} = 0$ and $\beta_{11ci} = \beta_{12ci} = \beta_{13ci} = \beta_{14ci} = 0$ in the external influence formulation, $\beta_{21i} = \beta_{22i} = \beta_{23i} = \beta_{24i} = 0$ and $\beta_{21ci} = \beta_{22ci} = \beta_{23ci} = \beta_{24ci} = 0$ in the internal influence formulation and $\beta_{41i} = \beta_{42i} = \beta_{43i} = \beta_{44i} = 0$ and $\beta_{41ci} = \beta_{42ci} = \beta_{43ci} = \beta_{44ci} = 0$ in the external and internal influence formulation, the longitudinal effects of marketing expenditures are not accommodated in the model. With these restrictions, the three formulations reduce to one model. This version is close to the traditional diffusion models where no promotional efforts are considered.

- Model versions 2E, 2I and 2EI: for these versions we employ the following restrictions:
(1) $\beta_{11i} = \beta_{12i} = \beta_{13i} = \beta_{14i}$ in the external influence formulation, $\beta_{21i} = \beta_{22i} = \beta_{23i} = \beta_{24i}$ in the internal influence formulation and $\beta_{41i} = \beta_{42i} = \beta_{43i} = \beta_{44i}$ in the external and internal influence formulation, own marketing instruments have the same effect on the trial rate, and (2) $\beta_{11ci} = \beta_{12ci} = \beta_{13ci} = \beta_{14ci} = 0$ in the external influence formulation, $\beta_{21ci} = \beta_{22ci} = \beta_{23ci} = \beta_{24ci} = 0$ in the internal influence formulation and $\beta_{41ci} = \beta_{42ci} = \beta_{43ci} = \beta_{44ci} = 0$ in the external and internal influence formulation, the longitudinal effects of competitors' marketing expenditures are not accommodated in the model. The external influence formulation -model 2E- corresponds to HPKZ2, the second specification of the model proposed by Hahn et al. (1994).

- Model versions 3E, 3I and 3EI: for these versions we employ the following restrictions:
$\beta_{11i} = \beta_{12i} = \beta_{13i} = \beta_{14i}$ and $\beta_{11ci} = \beta_{12ci} = \beta_{13ci} = \beta_{14ci}$ in the external influence formulation, $\beta_{21i} = \beta_{22i} = \beta_{23i} = \beta_{24i}$ and $\beta_{21ci} = \beta_{22ci} = \beta_{23ci} = \beta_{24ci}$ in the internal influence formulation and $\beta_{41i} = \beta_{42i} = \beta_{43i} = \beta_{44i}$ and $\beta_{41ci} = \beta_{42ci} = \beta_{43ci} = \beta_{44ci}$ in the external and internal influence formulation, we assume that all the marketing instruments have the same effect on the trial rate. In contrast to the previous versions, these versions allow for both own-brand and competing-brands promotional effects.

- Model versions 4E, 4I and 4EI: for these versions we employ the following restrictions:
$\beta_{12i} = \beta_{13i} = \beta_{14i}$ and $\beta_{12ci} = \beta_{13ci} = \beta_{14ci}$ in the external influence formulation $\beta_{22i} = \beta_{23i} = \beta_{24i}$ and $\beta_{22ci} = \beta_{23ci} = \beta_{24ci}$ in the internal influence formulation and $\beta_{42i} = \beta_{43i}$

$= \beta_{44i}$ and $\beta_{42ci} = \beta_{43ci} = \beta_{44ci}$ in the external and internal influence formulation. With these assumptions, we assume that the marketing instruments that are aimed at the physician all have the same effect on the trial rate. However, these specifications accommodate differences in the effects of the consumer-directed and physician-directed instruments. These versions are more flexible than the previous ones because they disaggregate promotional efforts from both own and competing drugs into "pull" and "push" effects. In these specifications, direct-to-consumer advertising represents the "pull" effect and detailing, medical journal advertising and physician meetings represent the "push" effect.

- <u>Model versions 5E, 5I and 5EI</u>: these are unrestricted versions of (6.5), (6.6) and (6.7).
These versions are the most flexible versions as they allow for heterogeneity in the effects of the different marketing variables.

In Table 6.2 we present an overview of the versions of the model we consider.

Table 6.2.
Versions of the proposed model in its external, internal and external and internal influence formulations.

-------------- Model 1 --------------

$$s_{i,t} = \left[\beta_{10i} + \beta_{2i}\left[\frac{s_{i,t-1}}{m_t}\right]\right]\left[m_t - q_{i,t-1}\right] + \beta_{3i}q_{i,t-1}$$

$$q_{i,t} - q_{i,t-1} = s_{i,t} - \beta_{3i}q_{i,t-1}$$

-------------- Model 2 --------------

External influence (Model 2E)

$$s_{i,t} = \left[\beta_{10i} + \beta_{11i}\ln\left(x_{i\bullet t}\right) + \beta_{2i}\left[\frac{s_{i,t-1}}{m_t}\right]\right]\left[m_t - q_{i,t-1}\right] + \beta_{3i}q_{i,t-1}$$

$$q_{i,t} - q_{i,t-1} = s_{i,t} - \beta_{3i}q_{i,t-1}$$

Internal influence (Model 2I)

$$s_{i,t} = \left[\beta_{10i} + \left(\beta_{2i} + \beta_{21i}\ln\left(x_{i\bullet t}\right)\right)\left[\frac{s_{i,t-1}}{m_t}\right]\right]\left[m_t - q_{i,t-1}\right] + \beta_{3i}q_{i,t-1}$$

$$q_{i,t} - q_{i,t-1} = s_{i,t} - \beta_{3i}q_{i,t-1}$$

External and internal influence (Model 2EI)

$$s_{i,t} = \left[\beta_{10i} + \beta_{2i}\left[\frac{s_{i,t-1}}{m_t}\right]\right]\left(1 + \beta_{41i}\ln\left(x_{i\bullet t}\right)\right)\left[m_t - q_{i,t-1}\right] + \beta_{3i}q_{i,t-1}$$

$$q_{i,t} - q_{i,t-1} = s_{i,t} - \beta_{3i}q_{i,t-1}$$

where $x_{i\bullet t} = \sum_{j=1}^{4} x_{ij,t}$

Table 6.2.
Versions of the proposed model in its external, internal and external and internal influence formulations (continued).

-------------- Model 3 --------------

External influence (Model 3E)

$$s_{i,t} = \left[\beta_{10i} + \beta_{11i}\ln\left(x_{i\bullet t}\right) + \beta_{11ci}\ln\left(x_{c\bullet t}\right) + \beta_{2i}\left[\frac{s_{i,t-1}}{m_t}\right]\right]\left[m_t - q_{i,t-1}\right] + \beta_{3i}q_{i,t-1}$$

$$q_{i,t} - q_{i,t-1} = s_{i,t} - \beta_{3i}q_{i,t-1}$$

Internal influence (Model 3I)

$$s_{i,t} = \left[\beta_{10i} + \left(\beta_{2i} + \beta_{21i}\ln\left(x_{i\bullet t}\right) + \beta_{21ci}\ln\left(x_{c\bullet t}\right)\right)\left[\frac{s_{i,t-1}}{m_t}\right]\right]\left[m_t - q_{i,t-1}\right] + \beta_{3i}q_{i,t-1}$$

$$q_{i,t} - q_{i,t-1} = s_{i,t} - \beta_{3i}q_{i,t-1}$$

External and internal influence (Model 3EI)

$$s_{i,t} = \left[\beta_{10i} + \beta_{2i}\left[\frac{s_{i,t-1}}{m_t}\right]\right]\left(1 + \beta_{41i}\ln\left(x_{i\bullet t}\right) + \beta_{41ci}\ln\left(x_{c\bullet t}\right)\right)\left[m_t - q_{i,t-1}\right] + \beta_{3i}q_{i,t-1}$$

$$q_{i,t} - q_{i,t-1} = s_{i,t} - \beta_{3i}q_{i,t-1}$$

where $x_{i\bullet t} = \sum_{j=1}^{4} x_{ij,t}$ and $x_{c\bullet t} = \sum_{j=1}^{4} x_{cj,t}$

-------------- Model 4 --------------

External influence (Model 4E)

$$s_{i,t} = \left[\beta_{10i} + \beta_{11i}\ln\left(x_{i1,t}\right) + \beta_{12i}\ln\left(x_{i\bullet t}\right) + \beta_{11ci}\ln\left(x_{c1,t}\right) + \beta_{12ci}\ln\left(x_{c\bullet t}\right) + \left(\beta_{2i}\left[\frac{s_{i,t-1}}{m_t}\right]\right)\right]\left[m_t - q_{i,t-1}\right] + \beta_{3i}q_{i,t-1}$$

$$q_{i,t} - q_{i,t-1} = s_{i,t} - \beta_{3i}q_{i,t-1}$$

Internal influence (Model 4I)

$$s_{i,t} = \left[\beta_{10i} + \left(\beta_{2i} + \beta_{21i}\ln\left(x_{i1,t}\right) + \beta_{22i}\ln\left(x_{i\bullet t}\right) + \beta_{21ci}\ln\left(x_{c1,t}\right) + \beta_{22ci}\ln\left(x_{c\bullet t}\right)\right)\left[\frac{s_{i,t-1}}{m_t}\right]\right]\left[m_t - q_{i,t-1}\right] + \beta_{3i}q_{i,t-1}$$

$$q_{i,t} - q_{i,t-1} = s_{i,t} - \beta_{3i}q_{i,t-1}$$

External and internal influence (Model 4EI)

$$s_{i,t} = \left[\beta_{10i} + \beta_{2i}\left[\frac{s_{i,t-1}}{m_t}\right]\right]\left(1 + \beta_{41i}\ln\left(x_{i1,t}\right) + \beta_{42i}\ln\left(x_{i\bullet t}\right) + \beta_{41ci}\ln\left(x_{c1,t}\right) + \beta_{42ci}\ln\left(x_{c\bullet t}\right)\right)\left[m_t - q_{i,t-1}\right] + \beta_{3i}q_{i,t-1}$$

$$q_{i,t} - q_{i,t-1} = s_{i,t} - \beta_{3i}q_{i,t-1}$$

where $x_{i\bullet t} = \sum_{j=2}^{4} x_{ij,t}$ and $x_{c\bullet t} = \sum_{j=2}^{4} x_{cj,t}$

Table 6.2.
Versions of the proposed model in its external, internal and external and internal influence formulations (continued).

------------- Model 5 -------------

External influence (Model 5E)

$$s_{i,t} = \left[\beta_{10i} + \sum_{j=1}^{4} \beta_{1ji} \ln\left(x_{ij,t}\right) + \sum_{j=1}^{4} \beta_{1jci} \ln\left(x_{cj,t}\right) + \beta_{2i} \left[\frac{s_{i,t-1}}{m_t} \right] \right] \left[m_t - q_{i,t-1} \right] + \beta_{3i} q_{i,t-1}$$

$$q_{i,t} - q_{i,t-1} = s_{i,t} - \beta_{3i} q_{i,t-1}$$

Internal influence (Model 5I)

$$s_{i,t} = \left[\beta_{10i} + \left(\beta_{2i} + \sum_{j=1}^{4} \beta_{2ji} \ln\left(x_{ij,t}\right) + \sum_{j=1}^{4} \beta_{2jci} \ln\left(x_{cj,t}\right) \right) \left[\frac{s_{i,t-1}}{m_t} \right] \right] \left[m_t - q_{i,t-1} \right] + \beta_{3i} q_{i,t-1}$$

$$q_{i,t} - q_{i,t-1} = s_{i,t} - \beta_{3i} q_{i,t-1}$$

External and internal influence (Model 5EI)

$$s_{i,t} = \left[\beta_{10i} + \beta_{2i} \left[\frac{s_{i,t-1}}{m_t} \right] \right] \left(1 + \sum_{j=1}^{4} \beta_{4ji} \ln\left(x_{ij,t}\right) + \sum_{j=1}^{4} \beta_{4jci} \ln\left(x_{cj,t}\right) \right) \left[m_t - q_{i,t-1} \right] + \beta_{3i} q_{i,t-1}$$

$$q_{i,t} - q_{i,t-1} = s_{i,t} - \beta_{3i} q_{i,t-1}$$

In Table 6.3 we present an overview of the marketing instruments that are incorporated in the LRK, the MWS, in the HPKZ models, and in our model.

Table 6.3.
Marketing communication characteristics of the trial-repeat diffusion models.

	Lilien, Rao and Kalish model (1981)	Mahajan, Wind and Sharma model (1983)	Hahn, Park, Krishnamurthi and Zoltners model (1994)	Proposed model
Marketing Communication:				
-"Push" strategy	Detailing	Not included	Detailing Medical journal advertising	Detailing Medical journal advertising Physician meetings
-"Pull" strategy	Not included	Not included	Not included	Direct-to-consumer advertising
-Heterogeneity in the effects of the marketing activities	No	No	No	Yes
-Competitor's marketing activities (separated from own)	Yes	No	No	Yes
-Influence on the trial rate through…				
…the external influence	Considered	Not considered	Considered	Considered
…the internal influence	Not considered	Not considered	Not considered	Considered
…both the external and internal influences[(1)]				Considered

(1): This indicates that separate models are proposed to test each alternative on the trial rate.

6.5. Sample, data and measurement of the variables

We use monthly US data on a category of prescription drugs, "rhinitis" category, to estimate the versions of the proposed model. Rhinitis is a reaction that occurs in the eyes, nose and throat when airborne irritants -allergens- trigger the release of histamine; histamine causes inflammation and fluid production in the fragile linings of nasal passages, sinuses, and eyelids. All the drugs in the category are functionally equivalent, i.e. they all treat the same medical symptoms. This category is highly competitive containing only branded products with small to moderate differences in price positioning[7]. The category is also characterized by a

[7] The average category price (in constant dollars) is 34.26$, the lowest average price is 25.67 (*Zyrec Syrup*) and highest price is 47.28$ (*Claritin*).

large number of introductions: it contains 16 products, 14 of which are introduced in the observational period (1993-2000). Thus, it is an appropriate category to validate the proposed model since we observe almost the complete category (87.5% of the drugs) from its inception (see Table 6.4). These introductions are accompanied by extensive marketing expenditures. The introductions differ in terms of instruments used and in terms of "money spent" per instrument. This allows us to study the effect of pharmaceutical marketing on diffusion of new drugs without the possible disturbance of differences in markets, differences in "seriousness" of the treated disease, etc.

Table 6.4.
Rhinitis category.

Brand ID	Name	Month of introduction
1	*Allegra*	August 1996
2	*Allegra-D*	January 1998
3	*Astelin*	January 1997
4	*Atrovent Nasal Spra*	December 1995
5	*Beconase*	before January 1993
6	*Claritin*	April 1993
7	*Claritin D*	November 1994
8	*Claritin Syrup*	October 1996
9	*Flonase*	December 1994
10	*Nasacort*	January 1993
11	*Nasarel*	October 1995
12	*Nasonex*	October 1997
13	*Rhinocort*	June 1994
14	*Vancenase*	before January 1993
15	*Zyrtec*	January 1996
16	*Zyrtec Syrup*	November 1996

The data set contains the following information for each drug: sales, price[8] and expenditures for detailing, medical journal advertising, physician meetings and direct-to-consumer advertising. Expenditures on advertising directed at physicians are higher than direct-to-consumer advertising, and detailing is the primary promotional activity directed at physicians. However, for the majority of the brands, expenditures on direct-to-consumer advertising are higher than expenditures on medical journal advertising and physician meetings, respectively.

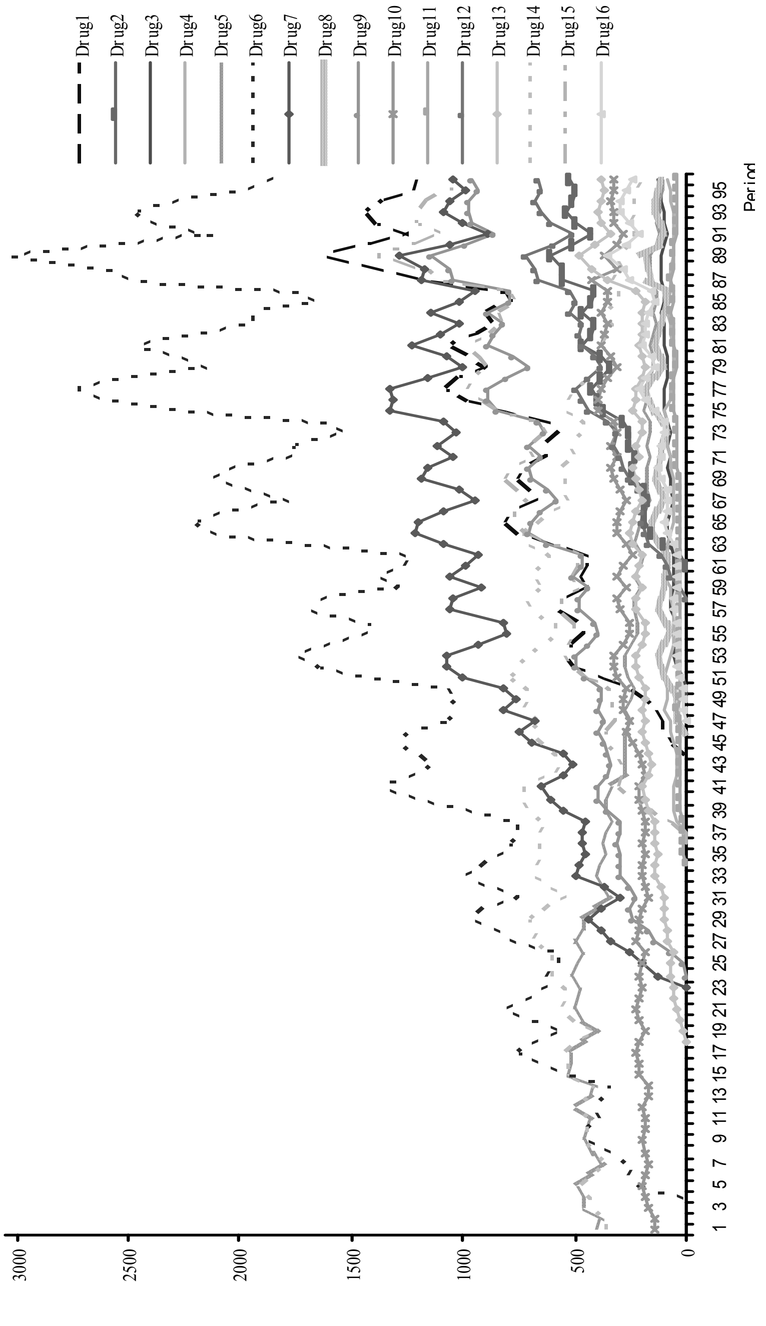
[8] Given that patient may need different dosages of a drug, price refers to the complete treatment course instead of per dose.

Figure 6.1 presents real monthly sales data of the new brands. Marketing variables are defined in terms of constant dollars and sales are seasonally adjusted[9] prior to estimating each of the parameters. We deflate the promotional expenditures by the Consumer Price Index (1982 = 1.00) to obtain the real expenditures for each drug in constant dollars. The seasonal adjustment (we use the Census X-11 seasonal adjustment method) allows for removing jumps in the sales time series that are not the result of marketing actions or inter-personal communication. As expenditures for promotional activities in a period influence the drug's sales in the following period, we have lagged the promotional activities by one month. The same number of lags is taken by Lilien, Rao and Kalish (1981) and Hahn et al. (1994). Although authors such as Gönül et al. (2001), Van den Bulte and Lilien (2001) and Berndt, Pindyck and Azoulay (2003) use marketing stock variables with a different number of lags to account for carryover effects in the promotional activities, the specification of our model already incorporates the lagged effects of marketing instruments. We also estimated versions of the model using stock variables with a different number of lags, but the option of one lag offered the best results. Natural logarithms are applied to marketing variables[10] to incorporate diminishing returns to scale for marketing actions in the model (Hahn et al., 1994).

[9] We apply a seasonal adjustment following Lilien, Rao and Kalish (1981) and Rao and Yamada (1988) instead of using the approach proposed by Hahn et al. (1994) of dividing sales by the growth of the usage rate over time. We proceed in this way for the following two reasons: i) the approach proposed by Hahn et al. (1994) does not deseasonalize our data, and ii) this approach takes out the market growth, so that category expansion effects would be removed from the data.

[10] We consider the marketing variables in a "mean deviation form".

Figure 6.1.
Real monthly data sales for the new drugs.



In Sections 6.2 and 6.4 we discussed some reasons for not including price in our model. Looking at the data of the rhinitis category we find three more arguments. Firstly, there are no generic drugs within this category (see Section 6.2). Secondly, we observe small differences in price positioning among the drugs. This seems to indicate that if there are no big differences in the price of competing drugs, factors other than price, such as advertising, are used by firms to compete. Price does not seem to be a key factor in this category to influence the switching from one branded drug to another. Thirdly, multicollinearity problems appeared when we included both price and the other marketing instruments in the model.

Although we focus on the rhinitis category, an especially interesting category given the large number of introductions (14 out of 16 drugs) in the period 1993-2000, we also calibrate the model on another two categories: osteoarthritis-rheumatoid-arthritis and asthma. These two categories together with rhinitis belong to the "Top-10 market" of prescription drugs in the US in 2000; i.e. the 10 major categories of prescription drugs that have the prescription drugs with the largest amount of sales among those with annual sales of 25$ million or more in the US in 2000. Although osteoarthritis-rheumatoid-arthritis and asthma categories have a lower proportion of new drugs than rhinitis (9 out of 20 drugs and 11 out of 26 drugs, respectively), they are also appropriate for calibration of our model for three reasons. First, these two categories use the same promotional instruments as rhinitis: detailing, medical journal advertising, physician meetings and also direct-to-consumer advertising. Second, it is interesting to analyze the results for other categories with similar and different characteristics to rhinitis. This is the case for osteoarthritis-rheumatoid-arthritis and asthma. The asthma category resembles the rhinitis category in terms of symptoms and seasonal patterns, whereas the osteoarthritis-rheumatoid-arthritis is completely different. Third, in contrast to the rhinitis category, the osteoarthritis-rheumatoid-arthritis category and the asthma category contain both branded drugs and generic drugs. Table 6.5 shows code (identification number of the drug), name, kind of drug (branded or generic drug) and introduction month for each drug within each category.

Table 6.5.
Osteoarthritis-rheumatoid-arthritis and asthma categories.

osteoarthritis-rheumatoid-arthritis				asthma			
Code	Name	kind	Month of introduction	Code	Name	kind	Month of introduction
1	*Arthrotec*	branded	January 1998	1	*Accolate*	branded	October 1996
2	*Celebrex*	branded	January 1999	2	*Aerobid*	branded	before January 1993
3	*Daypro*	branded	January 1993	3	*Albuterol Aerosol*	generic	January 1996
4	*Diclofenac Sodium*	generic	August 1995	4	*Albuterol Neb Soln*	generic	before January 1993
5	*Etodolac*	generic	March 1997	5	*Albuterol Oral*	generic	before January 1993
6	*Ibuprofen*	generic	before January 1993	6	*Atrovent Inh/Neb Sol*	branded	before January 1993
7	*Indomethacin*	generic	before January 1993	7	*Azmacort*	branded	before January 1993
8	*Ketoprofen*	generic	before January 1993	8	*Beclovent*	branded	before January 1993
9	*Lodine*	branded	before January 1993	9	*Combivent*	branded	June 1997
10	*Methylprednis Tabs*	generic	before January 1993	10	*Cromolyn Sod*	generic	May 1994
11	*Naprelan*	branded	April 1996	11	*Flovent*	branded	July 1996
12	*Naproxen*	generic	September 1993	12	*Intal*	branded	before January 1993
13	*Oruvail*	branded	October 1993	13	*Ipratropium Bromide*	generic	June 1996
14	*Piroxicam*	generic	before January 1993	14	*Maxair*	branded	before January 1993
15	*Prednisolone*	generic	before January 1993	15	*Proventil Aerosol*	branded	before January 1993
16	*Prednisone*	generic	before January 1993	16	*Proventil Oral*	branded	before January 1993
17	*Relafen*	branded	before January 1993	17	*Pulmicort Turbuhale*	branded	October 1997
18	*Sulindac*	generic	before January 1993	18	*Serevent*	branded	March 1994
19	*Vioxx*	branded	May 1999	19	*Serevent Diskus*	branded	December 1997
20	*Voltaren*	branded	before January 1993	20	*Singulair*	branded	March 1998
				21	*Theo-Dur*	branded	before January 1993
				22	*Theophylline SR*	generic	before January 1993
				23	*Uniphyl*	branded	before January 1993
				24	*Vanceril*	branded	before January 1993
				25	*Ventolin*	branded	before January 1993
				26	*Volmax*	branded	October 1993

6.6. Empirical results

6.6.1. Longitudinal effects of marketing instruments

We estimated the thirteen versions of the proposed model -Equations (6.5), (6.7) and (6.8)- (see Table 6.2) using the iterative OLS procedure[11] of Hahn et al. (1994). The estimation of models 2EI, 3EI, 4EI and 5EI -external and internal influence formulation- suffers from multicollinearity of the marketing instruments. Hence, we discard the external and internal influence formulation and compare the external with the internal formulations of model 2, 3, 4 and 5 using the Akaike Information Criterion and taking into account the face validity of the estimates. After selecting the best formulation -external or internal influence-, the likelihood ratio tests allow us to identify the most parsimonious specification (Ramanathan, 1993) between the nested versions of the models. The restricted model is defined as the null hypothesis and the unrestricted model as the alternative hypothesis. Table 6.6 summarizes the hypotheses for the likelihood ratio tests.

Table 6.6.
Hypotheses for the likelihood ratio tests (external influence formulation)[(1)].

Null hypothesis	Alternative hypothesis			
	Model 2	Model 3	Model 4	Model 5
Model 1	$\beta_{11i} = 0$	$\beta_{11i} = 0$ $\beta_{11ci} = 0$	$\beta_{11i} = \beta_{12i} = 0$ $\beta_{11ci} = \beta_{12ci} = 0$	$\beta_{11i} = \beta_{12i} = \beta_{13i} = \beta_{14i} = 0$ $\beta_{11ci} = \beta_{12ci} = \beta_{13ci} = \beta_{14ci} = 0$
Model 2		$\beta_{11ci} = 0$	$\beta_{12i} = 0$ $\beta_{11ci} = \beta_{12ci} = 0$	$\beta_{12i} = \beta_{13i} = \beta_{14i} = 0$ $\beta_{11ci} = \beta_{12ci} = \beta_{13ci} = \beta_{14ci} = 0$
Model 3			$\beta_{12i} = 0$ $\beta_{12ci} = 0$	$\beta_{12i} = \beta_{13i} = \beta_{14i} = 0$ $\beta_{12ci} = \beta_{13ci} = \beta_{14ci} = 0$
Model 4				$\beta_{13i} = \beta_{14i} = 0$ $\beta_{13ci} = \beta_{14ci} = 0$

(1): Identical hypotheses are used for the internal influence formulation.

The estimation of models 4E, 4I, 5E and 5I suffers from multicollinearity of the marketing instruments; the models as a whole are highly significant whereas the number of significant estimates is small. Other researchers find the same. For

[11] Since $q_{i,t\text{-}1}$ is not directly observeable from the data and as it is therefore not posible to estimate the parameters, we follow the procedure proposed by Hahn et al. (1994) to calculate it.

example Lilien, Rao and Kalish (1981), Gatignon, Weitz and Bansal (1990), Hahn et al. (1994), and Rizzo (1999) also report that marketing activities are highly correlated in pharmaceutical markets. We discard models 4 and 5, and continue investigating models 1, 2 and 3. The Akaike Information Criterion (Table 6.7) reveals that, although differences are very small, the external influence formulation is the most appropriate for the majority of the drugs for both models 2 and 3. Model 2E is preferred to model 2I in 11 out of 14 cases (79%) and Model 3E is preferred to model 3I in 10 out of 14 cases (71%). Face validity is quite similar for the external and internal influence formulations.

Table 6.7.
Akaike Information Criterion.

	model 2			model 3		
Brand code	model 2E	model 2I	preferred model	model 3E	model 3I	preferred model
10	9.70	9.71	model 2E	9.72	9.64	model 3I
6	11.63	11.62	model 2I	11.25	11.26	model 3E
13	8.38	8.46	model 2E	7.90	8.31	model 3E
7	12.27	12.28	model 2E	11.43	11.63	model 3E
9	9.73	9.75	model 2E	9.19	9.32	model 3E
11	3.97	4.04	model 2E	3.85	3.97	model 3E
4	5.55	5.55	model 2E	5.57	5.55	model 3I
15	9.67	9.68	model 2E	9.68	9.69	model 3E
1	10.65	10.66	model 2E	10.52	10.57	model 3E
8	5.95	5.96	model 2E	5.87	5.89	model 3E
16	7.02	7.01	model 2I	7.06	7.04	model 3I
3	7.83	7.84	model 2E	7.62	7.70	model 3E
12	8.59	8.67	model 2E	8.62	8.72	model 3E
2	10.80	10.79	model 2I	10.73	10.70	model 3I

The estimation results of models 1, 2E and 3E are shown in Tables 6.8, 6.9 and 6.10, respectively. These tables are divided into five column-blocks. Column-block 1 shows the identification numbers of the brands (the results are presented in order of introduction). Brands 5 and 14 were already on the market at the start of the observational period, so we cannot study their entire diffusion process. For that reason, those brands are not present in the tables. Column-block 2 contains the trial rate parameters, differentiating between external (β_{10i} in model 1, β_{10i} and β_{11i} in model 2E, and β_{10i}, β_{11i} and β_{11ci} in model 3E) and internal influence (β_{2i}). Column-block 3 shows the repeat rate parameter (β_{3i}). Column-block 4 presents the average market share of each brand. This column can be used to judge the face validity of the repeat rate, as the market share should approach the repeat rate. Column-block 5 presents the goodness-of-fit statistics (mean absolute deviation -MAD-, mean absolute percentage error -MAPE- and the correlation between the real and the estimated values of the dependent variables[12] -r-). All of the values in Tables 6.8, 6.9 and 6.10 are significantly different from zero ($\alpha = 0.0001$, $\alpha = 0.001$, $\alpha = 0.05$ or $\alpha = 0.10$). The results in Table 6.8, 6.9 and 6.10 are obtained using the marketing variables in a "mean deviation form": this creates values for β_{10i} that are comparable across brands and that can be interpreted as the basic propensity to try the new product (or innate innovativeness) when the marketing variables are at their mean level and when there is no internal influence. We performed several residual diagnostic checks, and concluded that neither the homoskedasticity, nor the non-normality assumption is violated. For some brands, the residuals show positive autocorrelation. We re-estimated the models for these brands using GLS, and observed only minor changes in the estimation results.

Table 6.8.
Estimation results of model 1.

Brand code	Trial rate: External influence $\hat{\beta}_{10i}$	Trial rate: Internal influence $\hat{\beta}_{2i}$	Repeat rate $\hat{\beta}_{3i}$	Average market share (in units)	MAD	MAPE	r
10	-0.05^{***}	1.31^{***}	0.09^{***}	0.04	23.38	9.03	0.92
6			0.32^{***}	0.20	63.83	4.76	0.99
13	-0.03^{***}	2.06^{***}	0.03^{***}	0.03	12.37	6.29	0.97
7		0.78^{*}	0.16^{***}	0.13	72.40	8.53	0.97
9	0.01^{o}	0.64^{***}	0.10^{***}	0.09	18.88	3.37	0.99
11		1.02^{***}	0.003^{**}	0.01	1.10	2.91	0.99
4	0.01^{***}	0.84^{***}	0.001^{*}	0.01	1.66	2.53	0.95
15	0.04^{***}	0.19^{o}	0.13^{***}	0.10	13.80	2.07	0.99
1	0.03^{**}		0.19^{***}	0.11	21.80	2.96	0.99
8	0.01^{***}	0.65^{***}	0.01^{o}	0.02	2.07	1.82	0.97
16	0.002^{*}	0.60^{***}	0.05^{***}	0.02	2.09	1.61	0.99
3	0.004^{**}	0.56^{***}	0.01^{*}	0.01	2.97	3.81	0.90
12	0.01^{***}	0.53^{***}	0.09^{***}	0.06	4.62	1.18	0.99
2	0.01^{*}	0.66^{**}	0.06^{***}	0.05	8.71	2.49	0.95

***: $p \leq 0.0001$; **: $p \leq 0.001$; *: $p \leq 0.05$; ^{o}: $p<0.1$

[12] We show r instead of R^2 or adjusted-R^2 since the proposed models do not have an intercept term (Judge et al., 1985, pp. 30-31).

The estimates in Table 6.8 correspond to outcomes of an earlier meta study conducted by Sultan, Farley and Lehmann (1990). They found that values for β_{10i} are positive and (much) smaller than the internal influence coefficient ($\hat{\beta}_{2i}$). This is the case for all but two of the significant estimates for β_{10i}. The significant estimates of β_{2i} are also within the expected range (positive and larger than β_{10i}). Also, the estimates of β_{3i} are reasonable, as they typically closely resemble the average market share of each brand. All of the differences between $\hat{\beta}_{3i}$ and the average market share are equal to or smaller than 0.08, except for brand 6, where the difference equals 0.12. The values for r, SSR and MAPE suggest that model 1 describes the diffusion process of the drugs in the rhinitis category quite well.

Table 6.9.
Estimation results of model 2E.

Brand code	Trial rate: External influence $\hat{\beta}_{10i}$	Trial rate: External influence $\hat{\beta}_{11i}$	Trial rate: Internal influence $\hat{\beta}_{2i}$	Repeat rate $\hat{\beta}_{3i}$	Average market share (in units)	MAD	MAPE	r
10	0.04^{***}		1.32^{***}	0.09^{***}	0.04	22.80	8.80	0.92
6		-0.03^{*}		0.31^{***}	0.20	61.30	4.57	0.99
13	0.04^{***}	0.01^{***}	1.65^{***}	0.03^{*}	0.03	8.84	4.49	0.99
7	0.07^{*}		0.88^{*}	0.16^{**}	0.13	72.76	8.57	0.98
9	0.07^{***}		0.59^{***}	0.10^{***}	0.09	18.36	3.27	0.99
11	0.01^{***}	0.0003^{***}	0.91^{***}	0.004^{**}	0.01	0.85	2.24	0.99
4	0.01^{***}		0.83^{***}	0.001^{***}	0.01	1.66	2.53	0.95
15	0.05^{***}		0.19^{o}	0.13^{***}	0.10	13.99	2.10	0.99
1	0.04^{***}			0.18^{***}	0.11	21.80	2.96	0.99
8	0.02^{***}	-0.001^{*}	0.57^{***}	0.01^{***}	0.02	1.87	1.65	0.98
16	0.01^{***}		0.59^{***}	0.05^{***}	0.02	2.09	1.62	0.99
3	0.01^{***}		0.54^{***}		0.01	3.05	3.91	0.90
12	0.03^{***}	0.002^{*}	0.42^{***}	0.09^{***}	0.06	4.38	1.11	0.99
2	0.04^{***}		0.65^{**}	0.06^{*}	0.05	8.50	2.43	0.95

***: $p \leq 0.0001$; **: $p \leq 0.001$; *: $p \leq 0.05$; ^{o}: $p<0.1$

The significant estimates of β_{10i} in Table 6.9 are also within the expected range. Three out of the five significant estimates for the effect of own marketing expenditures on the trial rate show a positive although small value; for two brands the estimated parameter is significant although negative; for nine brands, the estimated parameter turned out not to be significant. The significant estimates of β_{2i} are also within the expected range. The significant estimates of β_{3i} are reasonable. All of the differences between $\hat{\beta}_{3i}$ and the average market share are equal or smaller than 0.07, except for brand 6, which is 0.11. The values of r, SSR and MAPE indicate that model 2E also describes the adoption of the drugs in the rhinitis category well.

Table 6.10.
Estimation results of model 3E.

Brand code	Trial rate				Repeat rate	Average market share (in units)	MAD	MAPE	r
	External influence			Internal influence					
	$\hat{\beta}_{10i}$	$\hat{\beta}_{11i}$	$\hat{\beta}_{11ci}$	$\hat{\beta}_{2i}$	$\hat{\beta}_{3i}$				
10	0.04^{***}			1.29^{***}	0.01^{***}	0.03	22.81	8.81	0.92
6	0.09^{*}	0.02^{o}	-0.07^{***}		0.32^{***}	0.20	47.74	3.56	0.99
13	0.03^{***}	0.01^{***}	-0.01^{***}	1.47^{***}	0.04^{***}	0.03	7.17	3.65	0.99
7	0.07^{***}	0.02^{o}	-0.07^{***}	1.47^{***}	0.17^{***}	0.13	42.48	5.01	0.98
9	0.06^{***}	0.003^{**}	-0.02^{***}	0.63^{***}	0.11^{***}	0.09	13.53	2.41	0.99
11	0.01^{***}	0.0004^{***}	-0.0003^{*}	0.99^{***}	0.004^{***}	0.01	0.76	1.99	0.99
4	0.01^{***}			0.84^{***}		0.01	1.66	2.54	0.95
15	0.05^{***}			0.24^{*}	0.13^{***}	0.10	13.84	2.08	0.99
1	0.03^{***}	0.01^{*}	-0.01^{*}		0.19^{***}	0.11	19.59	2.66	0.99
8	0.02^{***}	-0.001^{**}	0.001^{*}	0.53^{***}	0.01^{***}	0.02	1.74	1.53	0.98
16	0.01^{***}			0.61^{***}	0.05^{***}	0.02	2.11	1.63	0.99
3	0.01^{***}	0.002^{*}	-0.003^{**}	0.39^{*}	0.02^{***}	0.01	3.28	4.20	0.93
12	0.03^{***}	0.002^{*}		0.40^{***}	0.09^{***}	0.06	4.38	1.11	0.99
2	0.03^{***}		-0.01^{*}	0.61^{**}	0.07^{***}	0.05	9.01	2.57	0.95

***: $p \leq 0.0001$; **: $p \leq 0.001$; *: $p \leq 0.05$; ^{o}: $p<0.1$

The results for model 3E provoke the following comments. The estimates of β_{10i} in Table 6.10 are all significant and within the expected range. All of the significant estimates for the effect of own marketing expenditures on the trial rate have the positive sign, except for brand 8, which is negative; for five brands, the estimated parameter turned out not to be significant. Competitors' marketing expenditures generally have a negative effect on the trial rate; for five brands, the estimated parameter turned out not to be significant. The significant estimates of β_{2i} are also within the expected range. Also, the values of $\hat{\beta}_{3i}$ are reasonable. All of the differences between $\hat{\beta}_{3i}$ and the average market share are equal or smaller than 0.08, except for brand 6, which is 0.12.

Results of the likelihood ratio tests are shown in Table 6.11. The second and third column of this table show the results of the likelihood ratio test for comparing model 1 -restricted model- and model 2E -unrestricted model-. For brand 10, the restriction, $\hat{\beta}_{11i} = 0$, does not lead to a significant decrease of fit (χ^2=1.48). Hence, model 1 is retained. For brand 6, χ^2=6.06 is significant and this indicates that model 2E is a significant improvement over model 1. Therefore, model 2E is retained.

Table 6.11.
Likelihood ratio tests.

Brand code	Restricted model: mod.1 Unrestricted model: mod.2E		Restricted model: mod.1 Unrestricted model: mod.3E		Restricted model: mod.2E Unrestricted model: mod.3E	
	χ^2	Retained model	χ^2	Retained model	χ^2	Retained model
10	1.48	model 1	1.66	model 1	0.18	model 2E
6	6.06*	model 2E	42.90*	model 3E	36.84*	model 3E
13	50.41*	model 2E	90.32*	model 3E	39.91*	model 3E
7	1.07	model 1	64.91*	model 3E	63.85*	model 3E
9	1.67	model 1	43.65*	model 3E	41.98*	model 3E
11	24.09*	model 2E	33.69*	model 3E	9.60*	model 3E
4	0.15	model 2E	0.68	model 1	0.54	model 2E
15	1.19	model 1	2.64	model 1	1.45	model 2E
1	0.50	model 1	9.18*	model 3E	8.68*	model 3E
8	7.36*	model 2E	13.07*	model 3E	5.71*	model 3E
16	0.02	model 1	0.24	model 1	0.22	model 2E
3	0.42	model 1	12.56*	model 3E	12.14*	model 3E
12	6.62*	model 2E	7.41*	model 3E	0.79	model 2E
2	0.05	model 1	4.74^{o}	model 3E	4.68*	model 3E

*: Significant at 0.05 level; ^{o}: Significant at 0.1 level.

Although there is not a model that has been retained for all the brands, in general terms model 3E is revealed as the preferred model (see Table 6.12) given that model 3E is a significant improvement over model 1 and model 2E in 71% and 64% of the cases, respectively.

Table 6.12.
Retained model -general terms-(1)

	Relative frequency
model 1 vs. model 2E	
model 1 is retained	8/14
model 2E is retained	6/14
model 1 vs. model 3E	
model 1 is retained	4/14
model 3E is retained	10/14
model 2E vs. model 3E	
model 2E is retained	5/14
model 3E is retained	9/14

(1): see Section 6.6.1 for an explanation about why external and internal formulations (EI models) are discarded.

We repeat the previous analyses for osteoarthritis-rheumatoid-arthritis and asthma categories. Again multicollinearity of the marketing instruments leads us to discard models 4 and 5, and continue investigating models 1, 2 and 3. The detailed results for these two categories are in Appendix 6A. Tables 6.13 and 6.14 show the summarized results for the three categories analyzed. Table 6A.1 (Appendix 6A) shows that, for the osteoarthritis-rheumatoid-arthritis category, internal influence formulation is preferred for model 2 in 6 out of 9 of the cases (67%) and for model 3 in 5 out of 9 of the cases (56%). Table 6A.2 (Appendix 6A) shows that, for the asthma category, external influence formulation is preferred for model 2 in 5 out of 10 of the cases (50%) and for model 3 in 8 out of 10 of the cases (56%)[13]. Face validity reveals that the external influence formulation shows more significant estimates with right signs and expected values. Face validity of the estimates is very relevant given that for the cross-section analysis (that we conduct in the following section) we use the estimates of the selected diffusion model in the longitudinal analysis carried out in this section. Table 6.13 summaries results for the three categories analyzed.

[13] Although within the asthma category there are 11 new drugs, the estimation method does not converge for drug 19. Hence, we retain the estimation results for 10 new drugs.

Table 6.13.
External vs. internal influence formulation.

	Akaike Information Criterion shows…… as the preferred formulation	Face validity shows…… as the preferred formulation
Rhinitis		
model 2	*External* influence formulation (in 11 out 14 of the cases)	*External* influence formulation and Internal influence formulation
model 3	*External* influence formulation (in 10 out 14 of the cases)	*External* influence formulation and Internal influence formulation
Osteoarthritis-rheumatoid-arthritis		
model 2	Internal influence formulation (in 6 out 9 of the cases)	*External* influence formulation
model 3	Internal influence formulation (in 5 out 9 of the cases)	*External* influence formulation
Asthma		
model 2	*External* influence formulation (in 5 out 10 of the cases)	*External* influence formulation
model 3	*External* influence formulation (in 8 out 10 of the cases)	*External* influence formulation

Table 6.13 shows that the external influence formulation is, in general terms, more appropriate than the internal influence formulation to describe the diffusion processes of the new drugs in the three categories analyzed. Appendix 6A shows the estimation results of models 1, 2E and 3E for osteoarthritis-rheumatoid-arthritis (Tables 6A.3, 6A.4 and 6A.5, respectively) and asthma (Tables 6A.6, 6A.7 and 6A.8, respectively). Appendix 6A also shows the likelihood ratio tests for osteoarthritis-rheumatoid-arthritis and asthma (Tables 6A.9 and 6A.10, respectively). Table 6.14 summaries the results of the likelihood ratio tests for the three categories analyzed. This table reveals that, in general terms, model 3E is the preferred model given that model 3E is a significant improvement over model 1 and model 2E in the three analyzed categories.

Table 6.14.
Retained model in each drug category -general terms-

	Rhinitis	Osteoarthritis-rheumatoid-arthritis	Asthma
	Relative frequency	Relative frequency	Relative frequency
model 1 vs model 2E			
model 1 is retained	8/14	5/9	7/10
model 2E is retained	6/14	4/9	3/10
model 1 vs model 3E			
model 1 is retained	4/14	0/9	4/10
model 3E is retained	10/14	9/9	6/10
model 2E vs model 3E			
model 2E is retained	5/14	0/9	4/10
model 3E is retained	9/14	9/9	6/10

From the results in this section we conclude that longitudinal effects of marketing instruments matter. The estimates of β_{1ji} and β_{1jci} show that the external influence on the trial rate varies over time: it responds to changes in both own and competitors' marketing expenditures. Own marketing expenditures increase the trial rate and competitors' marketing expenditures decrease the trial rate. We find that marketing efforts by the drug manufacturers are key drivers of the diffusion processes of the new drugs introduced into the market. In the next section we investigate whether there exist systematic differences in the parameter estimates between the brands. That is, we perform a second-stage cross-sectional analysis on the parameter estimates that we obtained in this section.

6.6.2. Cross-sectional effects of marketing instruments

It is of interest to investigate whether the basic propensity to try the new product - $\hat{\beta}_{10i}$ -, the physicians' internal influence parameter - $\hat{\beta}_{2i}$ - and the repeat rate[14] - $\hat{\beta}_{3i}$ - are influenced by the average own "marketing-pressure" during the introduction. In Section 6.2 we distinguished two functions of marketing communication that play a relevant role in the pharmaceutical industry: the "informative" and "persuasive" functions of pharma marketing. The "informative" function reveals that pharmaceutical marketing may influence the diffusion process

[14] Hahn at al. (1994, p. 235) refer to $\hat{\beta}_{3i}$ as "*the effectiveness of consumers' product trial or direct product experience on repeat purchase*".

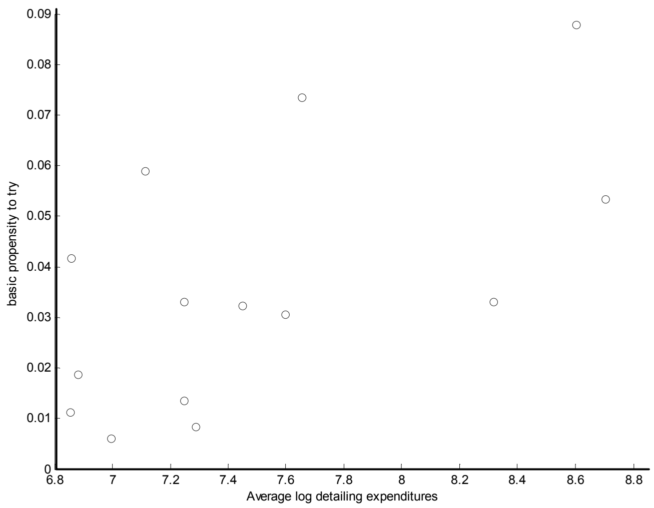
of a new product through the trial rate and the "persuasive" function through the repeat rate. We first investigate the trial rate ($\hat{\beta}_{10i}$ and $\hat{\beta}_{2i}$) during the first months after introduction and then the repeat rate ($\hat{\beta}_{3i}$) in two periods: 1) during the first months after introduction, and 2) during the complete period, given that the "persuasive" function refers to the influence that marketing activities have in creating market power for the promoted product.

We first explore the aforementioned relationships using scatter plots and correlation analysis. Subsequently we employ regression analysis. Analogous to the longitudinal analysis in Section 6.6.1 we present a detailed analysis for the rhinitis category and then provide a summary of the analyses of the osteoarthritis-rheumatoid-arthritis category and the asthma category.

Effects on the propensity to try and internal influence (trial rate)

Figure 6.2 shows a scatter plot of the estimated values of $\hat{\beta}_{10i}$ and the mean level of the own detailing expenditures during the first 12 months after introduction[15].

Figure 6.2.
Scatter plot of the basic propensity to try ($\hat{\beta}_{10i}$) and the mean of the log of detailing level.



[15] In Figure 6.2 and in the rest of this section, the estimation results of model 3E are used.

The correlation coefficient of the scatter plot in Figure 6.2 is significant with a confidence level of 95% (ρ = 0.60; p-value = 0.02), which indicates that the basic propensity to try the new product is positively affected by a high level of detailing during the first 12 months after introduction. The other marketing instruments show a similarly positive although not significant correlation with $\hat{\beta}_{10i}$, except physician meetings, which show a positive and significant correlation with $\hat{\beta}_{10i}$ (see Table 6.15).

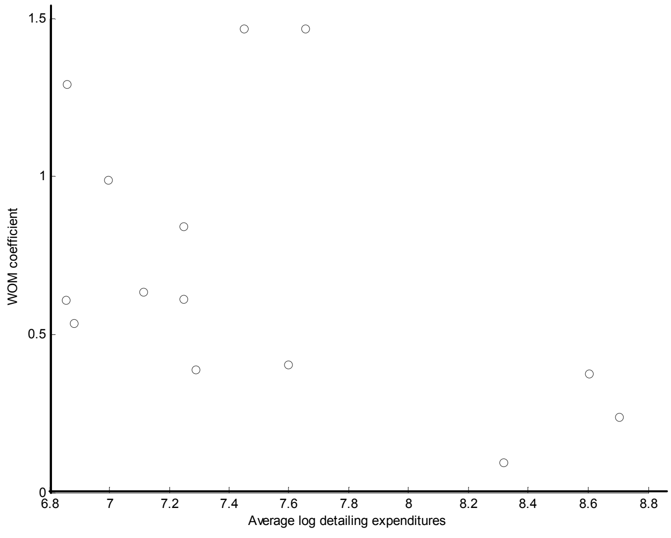
Table 6.15.
Correlation between marketing instruments and the basic propensity to try ($\hat{\beta}_{10i}$)

	ρ	p-value
detailing	0.60*	0.02
medical journal advertising	0.30	0.29
physician meetings	0.59*	0.03
direct-to-consumer advertising	0.10	0.73

*: $p \leq 0.05$

Figure 6.3 shows a scatter plot of the estimated values of $\hat{\beta}_{2i}$ and the mean level of the own detailing expenditures during the first 12 months after introduction.

Figure 6.3.
Scatter plot of the WOM coefficient ($\hat{\beta}_{2i}$) and the mean of the log of detailing level.



The correlation coefficient of the scatter plot of $\hat{\beta}_{2i}$ and the mean detailing level (see Figure 6.3) is not significant (ρ = -0.45; p-value = 0.10). We also do not find a significant correlation between physician meeting expenditures and $\hat{\beta}_{2i}$. This indicates that internal influence is not significantly affected by detailing or physician meeting expenditures during the first 12 months after introduction. The other two marketing instruments show a negative and significant correlation with $\hat{\beta}_{2i}$ (see Table 6.16). A possible explanation for the fact that detailing and physician meeting expenditures are not significantly correlated to $\hat{\beta}_{2i}$ is that these marketing activities provide sufficient information to physicians and internal influence loses importance. The negative correlation of $\hat{\beta}_{2i}$ and the other two instruments, medical journal advertising and direct-to-consumer advertising, is harder to explain. These results appear to be driven by a few brands that spend relatively large amounts on these instruments and have small estimates for β_{2i}.

Table 6.16.
Correlation between marketing instruments and the internal influence coefficient ($\hat{\beta}_{2i}$)

	ρ	p-value
detailing	-0.45	0.10
medical journal advertising	-0.55*	0.04
physician meetings	-0.36	0.21
direct-to-consumer advertising	-0.61*	0.02

*: $p \leq 0.05$

In order to check the insights revealed by the correlation analysis, we regress $\hat{\beta}_{10i}$ and $\hat{\beta}_{2i}$ on the marketing instruments and also on the order of entry of the brands into the marketplace. Seemingly Unrelated Regression (SUR) corrected by the approach developed by Wittink (1977) is used because this estimation method properly accounts for heteroscedasticity[16]. The SUR results (see Table 6.17) show that marketing activity and order of entry affect the trial rate of the new brands[17]. The marketing activity has a positive and significant effect on the basic propensity to try but a negative and significant effect on the internal influence. This suggests that the more marketing activity, the higher the propensity to try and the lower the

[16] Correction for heteroscedasticity is needed given that the dependent variables of the regressions are the parameter estimates from different brands (Wittink, 1977).
[17] We carried out this analysis considering the significant and not significant estimates of β_{2i}, and we repeat the same analysis by changing the not significant estimates to zeros. The results do not change.

effectiveness of the physicians' internal influence. As we mentioned earlier, the negative effect of marketing activity on internal influence seems to be driven by a few brands that spend relatively large amounts on marketing instruments and have small estimates for β_{2i}. This has to be further investigated. The order of entry effects are negative and significant for $\widehat{\beta}_{10i}$ and $\widehat{\beta}_{2i}$. This suggests that drugs launched early have advantages on the impact of the propensity to try and the internal influence, revealing the order of entry as an important strategic variable. As we expected, drugs launched early have a better opportunity to occupy a preferential position on the physicians' product space[18].

Table 6.17.
SUR results for the basic propensity to try ($\hat{\beta}_{10i}$) and the internal influence coefficient ($\hat{\beta}_{2i}$) -Aggregate marketing expenditures-

	$\hat{\beta}_{10i}$	$\hat{\beta}_{2i}$
constant	0.02	1.95***
marketing expenditures	0.002*	-0.05**
order of entry	-0.003*	-0.06*
R^2 (%)	51.56	66.41
R^2-adjusted (%)	42.75	60.30

***: p≤ 0.0001; **: p≤ 0.001; *: p≤ 0.05

Due to multicollinearity in the marketing instruments, the separated effects of expenditures in detailing, medical journal advertising, physician meetings and direct-to-consumer advertising could not be detected. Hence, we are not able to determine the impact of each marketing instrument on the trial rate. However, Table 6.18 shows the effects of the expenditures on direct-to-physician marketing -"push" strategy- and direct-to-consumer advertising -"pull" strategy- on $\hat{\beta}_{10i}$ and $\hat{\beta}_{2i}$. The expenditures in direct-to-physician marketing have a positive and significant effect on $\widehat{\beta}_{10i}$ and a negative although slightly significant effect on $\widehat{\beta}_{2i}$. However, the expenditures in direct-to-consumer advertising have a non-significant effect on $\hat{\beta}_{10i}$ but a negative although slightly significant effect on $\hat{\beta}_{2i}$. This suggests that direct-to-physician marketing has a relevant impact on $\hat{\beta}_{10i}$ and a

[18] We also tried a regression which considers, apart from marketing expenditures and order of entry, the cross effect between these variables; however, results did not improve nor show additional significant information. We also introduced a cross effect variable in subsequent regressions but, again, results did not improve nor show additional significant information.

slightly significant impact on $\hat{\beta}_{2i}$ during the first 12 months after introduction, but direct-to-consumer advertising only has a demonstrable impact (slightly significant) on internal influence.

Table 6.18.
SUR results for the basic propensity to try ($\hat{\beta}_{10i}$) and the internal influence coefficient ($\hat{\beta}_{2i}$) -Disaggregate marketing expenditures-

	$\hat{\beta}_{10i}$	$\hat{\beta}_{2i}$
constant	0.01	1.84***
direct-to-physician marketing expenditures	0.01*	-0.04^{o}
direct-to-consumer advertising expenditures	-0.002	-0.06^{o}
order of entry	-0.003*	-0.06*
R^2 (%)	63.15	66.80
R^2-adjusted (%)	52.10	56.84

***: p≤ 0.0001; **: p≤ 0.001; *: p≤ 0.05; ^{o}: p< 0.1

Our results show that, during the first 12 months after introduction:

i) the "informative" function of marketing activities is confirmed;
ii) the higher the marketing activities, the higher the propensity to try new brands;
iii) the higher the marketing activities, the lower the effectiveness of the physicians' internal influence.
iv) direct-to-consumer advertising expenditures ("pull" strategy) influence the propensity to try but have no demonstrable impact on internal influence.
v) the sooner a new drug enters the market, the higher the propensity to try and the higher the effectiveness of the physicians' internal influence.

Effects on the repeat rate

The cross-sectional effect of marketing expenditures is also related to the "persuasive" function of pharma marketing. This "persuasive" function influences the diffusion of a new product through the repeat rate. Table 6.19 shows the coefficients of the correlation between the average expenditures on each marketing instrument and the repeat rate during the first 12 months after introduction and for the complete period.

Table 6.19.
Correlation between marketing instruments and the repeat rate ($\hat{\beta}_{3i}$)

	12-month period		complete period	
	ρ	*p*-value	ρ	*p*-value
detailing	0.76*	0.002	0.76*	0.002
medical journal advertising	0.37	0.19	0.69*	0.01
physician meetings	0.62*	0.02	0.64*	0.01
direct-to-consumer advertising	0.23	0.43	0.75*	0.002

*: p≤ 0.05

Figures 6.4 and 6.5 show the scatter plots of the repeat rate and the mean detailing level for the 12-month and complete periods, respectively.

Figure 6.4.
Scatter plot of the repeat rate ($\hat{\beta}_{3i}$) and the mean of the log of detailing level (12-month period)

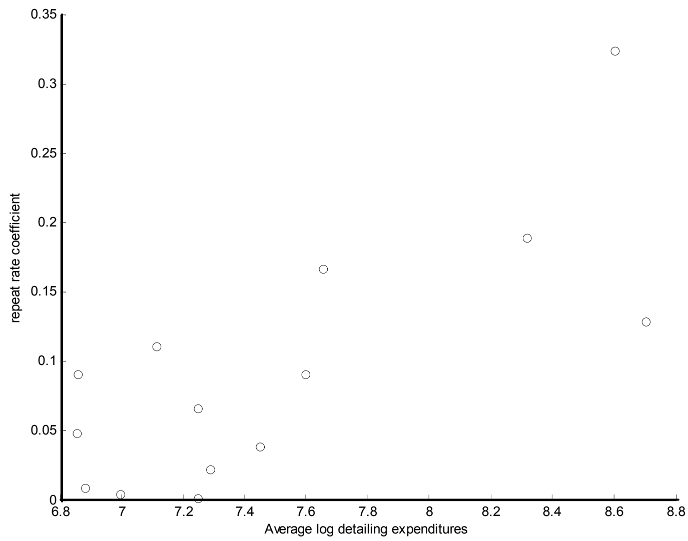


Figure 6.5.
Scatter plot of the repeat rate ($\hat{\beta}_{3i}$) and the mean of the log of detailing level (complete period)

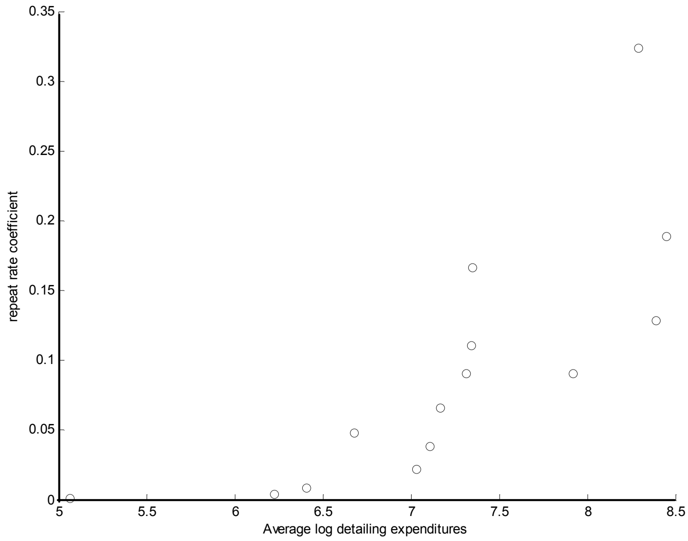


Table 6.19 shows that:

i) only direct-to-physician marketing (specifically, detailing and physicians meetings) is significantly correlated with the repeat rate shortly after introduction of the new product. However, for the complete period, all marketing instruments, including direct-to-consumer advertising, are significantly correlated with the repeat rate and show a high correlation; and

ii) the correlation between marketing instruments and the repeat rate increases when we consider the complete period.

Hence, results suggest that all marketing instruments are important in creating market power for the promoted drugs, although expenditures on direct-to-physician marketing ("push" strategy) show a more rapid influence on physicians than expenditures on direct-to-consumer advertising ("pull" strategy). Furthermore, expenditures on direct-to-consumer advertising appear to be important in creating market power for the promoted drugs. These results show the relevant role that a "pull" strategy plays in pharma marketing.

The SUR results (see Table 6.20) show that, both for the first 12 months after introduction and for the complete period, marketing expenditures have a positive and significant effect on the repeat rate. These results show that marketing activity has a rapid persuasive influence on physicians allowing pharmaceutical companies to protect themselves from competitor's products. The effect of the order of entry of the new brands into the marketplace is negative and significant for the 12-month period, but negative although not significant for the complete period. The results also show that an early entrance in the market creates barriers of entry during the first year after introduction. However, the order of entry loses importance for the complete period. This could be because, over time other aspects (such as the availability of the drug in a certain geographical area) are more important than the age of a drug (i.e. the time that the drug has been in the marketplace) to physicians' repeat prescription decisions. Furthermore, results show that the repeat rate is stronger related to marketing activities for the complete period than to marketing activities for the beginning of the period. This is expected given that the repeat rate is conceptually closer to the long run average market share of the new product.

Due to multicollinearity in the marketing instruments, we are not able to investigate the impact of each marketing instrument on the repeat rate. However, for the 12-month period (see Table 6.21), results reveal that the effect of direct-to-physician marketing is positive and significant and the effect of direct-to-consumer advertising is not significant[19]. Table 6.21 also shows the results for the complete period. The results seem to indicate, although not significant at the 5% level, that "pull" strategy becomes a barrier of entry for the complete period.

[19] We carried out this analysis (Tables 6.20 and 6.21) considering the significant and not significant estimates of β_{3i}, and we repeat the same analysis by changing the non significant estimates to zeros. The results do not change.

Table 6.20.
SUR results for the repeat rate ($\hat{\beta}_{3i}$)
-Aggregate marketing expenditures-

	$\hat{\beta}_{3i}$ 12-month period	$\hat{\beta}_{3i}$ complete period
constant	-0.004	-0.05
marketing expenditures	0.01*	0.01***
order of entry	-0.01*	-0.01
R^2 (%)	46.75	69.28
R^2-adjusted (%)	37.07	63.70

***: p≤ 0.0001; **: p≤ 0.001; *: p≤ 0.05

Table 6.21.
SUR results for the repeat rate ($\hat{\beta}_{3i}$)
-Disaggregate marketing expenditures-

	$\hat{\beta}_{3i}$ 12-month period	$\hat{\beta}_{3i}$ complete period
constant	-0.12	-0.03
direct-to-physician marketing expenditures	0.02*	0.01^{o}
direct-to-consumer advertising expenditures	-0.003	0.01^{o}
order of entry	-0.01^{o}	-0.01
R^2 (%)	56.48	69.46
R^2-adjusted (%)	43.42	60.29

*: p≤ 0.05; ^{o}: p< 0.1

6.6.2.1. Pooled cross-sectional analysis

We also carried out the cross-sectional analysis for the osteoarthritis-rheumatoid-arthritis and asthma categories. Because of the small number of new drugs in each category, the SUR estimation method does not show significant estimates, except for $\hat{\beta}_{3i}$ in osteoarthritis-rheumatoid-arthritis. To overcome this problem we pool the three categories and carry out a pooled SUR estimation method by allowing the constant term to vary across categories. Given that the osteoarthritis-rheumatoid-arthritis and asthma categories have branded and generic new drugs, we include the dummy "kind" (kind = 1 if the new product is a branded drug; kind = 0 if the new product is a generic drug) in the system. Tables 6.22 through 6.25 show the results.

Table 6.22 shows the effects of the marketing expenditures, the order of entry and the kind of drug (branded or generic drug) on $\hat{\beta}_{10i}$ and $\hat{\beta}_{2i}$ during the first 12 months after introduction. Table 6.23 shows the same effects but differentiates between direct-to-physician marketing and direct-to-consumer advertising. Again, due to multicollinearity in the marketing instruments, separate effects could not be investigated.

Table 6.22.
Pooled SUR results for the basic propensity to try ($\hat{\beta}_{10i}$) and the internal influence coefficient ($\hat{\beta}_{2i}$) -Aggregate marketing expenditures-

	$\hat{\beta}_{10i}$	$\hat{\beta}_{2i}$
constant – rhinitis category	0.08**	1.13**
constant – osteoarthritis-rheumatoid-arthritis category	0.06**	1.30***
constant – asthma category	0.06**	0.80*
marketing expenditures	0.004*	-0.03
order of entry	-0.002	-0.05*
kind	-0.08*	0.38
R^2 (%)	29.80	34.35
R^2-adjusted (%)	16.80	22.19

***: p≤ 0.0001; **: p≤ 0.001; *: p≤ 0.05

Table 6.23.
Pooled SUR results for the basic propensity to try ($\hat{\beta}_{10i}$) and the internal influence coefficient ($\hat{\beta}_{2i}$) -Disaggregate marketing expenditures-

	$\hat{\beta}_{10i}$	$\hat{\beta}_{2i}$
constant – rhinitis category	0.08**	1.10***
constant – osteoarthritis-rheumatoid-arthritis category	0.06*	1.21***
constant – asthma category	0.06*	0.73*
direct-to-physician marketing expenditures	0.005*	-0.01
direct-to-consumer advertising expenditures	0.001	-0.07
order of entry	-0.002	-0.04°
kind	-0.10*	0.13
R^2 (%)	31.46	37.34
R^2-adjusted (%)	15.64	22.88

***: p≤ 0.0001; **: p≤ 0.001; *: p≤ 0.05; °: p< 0.1

The results for $\hat{\beta}_{10i}$ and $\hat{\beta}_{2i}$ in the pooled cross-sectional analysis with aggregate marketing expenditures are similar to those when we differentiate between marketing directed at physicians and direct-to-consumer advertising. The coefficient for the variable "kind" is negative and significant for $\hat{\beta}_{10i}$. This indicates that generic new drugs tend to have a higher propensity to try than newly introduced branded drugs.

Table 6.24 shows the effects of the marketing expenditures, the order of entry and the kind of drug (branded or generic drug) on $\hat{\beta}_{3i}$ during the first 12 months after introduction and for the complete period. Table 6.25 shows the same effects but differentiates between direct-to-physician marketing and direct-to-consumer advertising during the first 12 months after introduction. Due to the correlation between both types of strategies we are not able to estimate their separate effects for the complete period.

Table 6.24.
Pooled SUR results for the repeat rate ($\hat{\beta}_{3i}$)
-Aggregate marketing expenditures-

	$\hat{\beta}_{3i}$ 12-month period	$\hat{\beta}_{3i}$ complete period
constant – rhinitis category	0.11^{o}	0.09*
constant – osteoarthritis-rheumatoid-arthritis category	0.04	0.06
constant – asthma category	0.10*	0.10*
marketing expenditures	0.01*	0.01***
order of entry	-0.004	-0.004
kind	-0.12^{o}	-0.14*
R^2 (%)	18.00	41.06
R^2-adjusted (%)	2.82	30.14

***: p≤ 0.0001; **: p≤ 0.001; *: p≤ 0.05; ^{o}: p< 0.1

Table 6.25.
Pooled SUR results for the repeat rate ($\hat{\beta}_{3i}$)
-Disaggregate marketing expenditures-

	$\hat{\beta}_{3i}$ 12-month period
constant – rhinitis category	0.10*
constant – osteoarthritis-rheumatoid-arthritis category	0.04
constant – asthma category	0.10^{o}
direct-to-physician marketing expenditures	0.01^{o}
direct-to-consumer advertising expenditures	0.005
order of entry	-0.003
kind	-0.14^{o}
R^2 (%)	18.29
R^2-adjusted (%)	-0.01

**: p≤ 0.001; *: p≤ 0.05; ^{o}: p< 0.1

The cross-section analyses for the three analyzed categories show similar results for the repeat rate during the first 12 months after introduction, whether we consider aggregate marketing expenditures or differentiate between marketing directed at physicians and direct-to-consumer advertising. We also get the same results for the complete period. As with the propensity to try, the results seem to confirm that, during the first 12 months after introduction, generic new drugs have advantages on the repeat rate. This result is also shown for the complete period.

In summary, the cross-sectional analysis for the three categories analyzed confirms the conclusions of the longitudinal analysis for the rhinitis category. The results of the pooled SUR analysis indicate that:

i) the "informative" and "persuasive" functions of marketing activities exist;
ii) the higher the marketing activities, the higher the propensity to try new brands;
iii) marketing activities have no demonstrable impact on the effectiveness of physicians' internal influence. A possible explanation for this could be that detailing, medical journal advertising and/or physician meetings provide sufficient information to physicians and internal influence loses importance.
iv) the higher the marketing activities, the higher the repeat rate (for the 12-month and complete periods);
v) marketing activities have a different impact on the trial rate during the first 12 months after introduction. The impact of marketing activities is higher on the repeat rate than on the propensity to try;
vi) direct-to-consumer advertising ("pull" strategy) seems neither to affect the internal influence, the propensity to try nor the repeat rate during the first 12 months after introduction;
vii) generic new drugs have advantages on the impact of the propensity to try and the repeat rate;
viii) order of entry has no demonstrable impact on the repeat and trial rates when the three categories are considered. Order of entry seems to be more important in the 'young' rhinitis category than in the other two 'older' categories, where a number of generic drugs compete with branded drugs.

6.6.3. Investigating a new approach: a recursive window approach

Our results show that marketing expenditures have an impact on the diffusion speed of pharmaceutical products. Multicollinearity problems do not allow for simultaneous investigation of the effect of marketing on all three diffusion parameters (external influence, internal influence and the repeat rate). In this subsection we employ a new approach that allows us to analyze the impact of the different marketing instruments on the diffusion parameters over time.

We start by considering the following extension of model 1 where the diffusion parameters are considered as time-varying parameters:

$$s_{i,t} = \left[\beta_{10i,t} + \beta_{2i,t}\left[\frac{s_{i,t-1}}{m_t}\right]\right]\left[m_t - q_{i,t-1}\right] + \beta_{3i,t}q_{i,t-1} \tag{6.8}$$

with $q_{i,t} - q_{i,t-1} = s_{i,t} - \beta_{3i}q_{i,t-1}$.

We estimate the extended model 1 -Equation (6.8)- by dividing the complete period of study (i.e. a time window of 96 observations) into a number of time windows. We try two approaches: 1) a recursive time window approach, and 2) a rolling time window approach. The recursive time window approach keeps the window origin fixed at the first time period in the sample and successively adds observations, thereby increasing the number of observations one by one. The rolling time window approach uses a fixed number of observations within each window and estimates the model in every window before moving on to the next (Swanson and White, 1997; Tashman, 2000). These two approaches are appealing from a diagnostic perspective, but also from a descriptive perspective given that we can use data available prior to a certain time to evaluate the marketing actions during that period. However, there is a characteristic of the rolling approach that makes this approach less appropriate than the recursive one: the rolling window removes the initial information (first observations) of the sample. This information is particularly relevant to represent the data generating process when we are analyzing the diffusion process of new products. Nevertheless, we investigate both approaches.

We estimate the model in Equation (6.8) using the recursive windows approach where the first window has 15 monthly observations (the minimum number of observations to properly estimate the model), we also use the rolling windows approach with windows of 25 monthly observations[20]. We employ scatter plots to explore the relationship between the estimates of the time-varying diffusion parameters ($\hat{\beta}_{10i,t}$, $\hat{\beta}_{2i,t}$ and $\hat{\beta}_{3i,t}$) and the mean level of expenditures on the different marketing instruments in each window: detailing, medical journal advertising, physician meetings, direct-to-consumer advertising, aggregate marketing (by adding all marketing instruments) and direct-to-physician marketing (by adding detailing, medical journal advertising and physician meetings). Results for the rolling window approach do not show any insights on the role that marketing actions play on the diffusion processes of the new drugs. However, the scatter plots using the recursive time window reveal interesting patterns. For

[20] The rolling window approach requires the choice of a window size taking into account that small sizes suffer from low test power and large sizes may not pick up changes early and late in the sample. We tried different window sizes (Pauwels and Hanssens, 2004).

example, a positive correlation between $\hat{\beta}_{10i,t}$ and expenditures on detailing for some drugs.

Appendix 6B presents several plots and summary tables of some of the new drugs in the rhinitis category that show the temporal pattern of the diffusion parameters, the temporal pattern of the different marketing instruments and the correlation among them. In general terms, for the complete category (14 new branded drugs), the plots show that $\hat{\beta}_{10i,t}$ and $\hat{\beta}_{3i,t}$ follow the same temporal tendency as the mean level of expenditures on marketing directed at physicians, especially detailing. However, $\hat{\beta}_{2i,t}$ shows contrary behavior to $\hat{\beta}_{10i,t}$ and $\hat{\beta}_{3i,t}$.

The scatter plots and the correlation analysis reveal that, in general terms, $\hat{\beta}_{10i,t}$ and $\hat{\beta}_{3i,t}$, show a positive and significant correlation with the mean level of expenditures on direct-to-physician marketing, particularly on detailing and physician meetings. There is no clear pattern for medical journal advertising nor for direct-to-consumer advertising (although for direct-to-consumer advertising there seems to be a positive correlation). The results show the opposite pattern for $\hat{\beta}_{2i,t}$, which is consistent with our results for the longitudinal and the cross-sectional analysis. In future research we plan to investigate these patterns in more detail further.

6.7. Conclusions

In this study, we investigate both longitudinal and cross-sectional effects of marketing expenditures on the diffusion of new pharmaceuticals in the "rhinitis"-category. We model the diffusion process of fourteen new brands that are introduced within the observational period. We also model the diffusion processes of new drugs in another two categories, one (asthma) similar and another (osteoarthritis-rheumatoid-arthritis) quite different from rhinitis.

We employ a family of trial-repeat diffusion models that allows us (1) to detect the appropriate allocation for marketing instruments in the trial rate, (2) to accommodate heterogeneity in the effects of the different marketing instruments, and (3) to accommodate a time-varying trial rate that is influenced by both own and competitors' marketing expenditures. In a second-stage analysis we determine the cross-sectional effects of marketing expenditures on the trial rate and on the repeat rate.

Using eight years of US monthly data we find support for the hypothesis that changes in the trial rate are positively related to changes in own marketing expenditures. We also find support for the hypothesis that the trial rate is negatively affected by competitors' marketing expenditures. The results indicate that, in general terms, the external influence formulation of the proposed trial-repeat diffusion model is the most appropriate to incorporate marketing variables for the three categories analyzed.

Besides these longitudinal effects we also find that cross-sectional differences in marketing expenditures are significantly affecting the trial rate and the repeat rate of the diffusion processes of new pharmaceutical products. Specifically, our results show that the mean level of marketing expenditures is positively related to the basic propensity to try the new product and to the repeat rate but apparently not related to the internal influence. These results hold for all three drug categories analyzed, except that in the case of rhinitis, marketing expenditures are negatively related to internal influence. These results imply that the basic propensity to try brands with a high level of marketing expenditures is larger than that of brands with a lower level of marketing expenditures. In addition, such effects exist for the repeat rate as well. However, the relationship is either non existent or the opposite for the internal influence. We argue that marketing expenditures both have an informative and persuasive influence on the diffusion of new products in the category under study. These results are in line with those of Narayanan, Manchanda and Chintagunta (2004) who find evidence for the presence of both indirect (informative) and direct (persuasive) effects of advertising. Furthermore, order of entry is confirmed to play an important role in the launch strategy of the new products in the rhinitis category, which has only branded drugs. However, when we consider the three categories, order of entry becomes less important. In this analysis we also find that generics tend to have a higher basic propensity to try, a larger effect of internal influence and a higher repeat rate than branded drugs.

Finally, we investigate the longitudinal patterns further using a recursive window approach. Preliminary results for the rhinitis category show that the marketing directed at physicians, especially for detailing, but also for physician meetings, is a key factor in determining the temporal pattern of the diffusion parameters. There seems not to be a clear pattern, for medical journal advertising, and for direct-to-consumer advertising. Apart from these preliminary results, which need future research, we are also investigating the effect of the different marketing instruments on the number of triers and repeaters of prescription drugs.

Appendix 6A. Some results of other categories

Tables 6A.1 and 6A.2 show the Akaike Information Criterion for models 2E, 2I, 3E and 3I for osteoarthritis-rheumatoid-arthritis and for asthma, respectively.

Table 6.A1.
Akaike Information Criterion -osteoarthritis-rheumatoid-arthritis-.

	model 2			model 3		
Brand code	model 2E	model 2I	preferred model	model 3E	model 3I	preferred model
3	11.27	10.53	model 2I	10.63	10.25	model 2I
12	11.99	11.92	model 2I	11.22	10.97	model 2I
13	9.77	9.49	model 2I	9.58	9.49	model 2I
4	11.23	11.18	model 2I	10.12	11.08	model 2E
11	7.56	6.55	model 2I	6.97	6.58	model 2I
5	7.44	7.45	model 2E	7.05	7.18	model 2E
1	8.29	8.24	model 2I	8.16	7.95	model 2I
2	11.79	12.24	model 2E	11.73	12.09	model 2E
19	10.39	10.52	model 2E	10.34	10.48	model 2E

Table 6.A2.
Akaike Information Criterion -asthma-.

	model 2			model 3		
Brand code	model 2E	model 2I	preferred model	model 3E	model 3I	preferred model
26	7.29	7.32	model 2E	7.13	7.35	model 2E
18	7.62	7.77	model 2E	7.64	7.78	model 2E
10	7.18	7.20	model 2E	7.15	7.17	model 2E
3	10.43	10.39	model 2I	10.38	10.32	model 2I
13	5.23	5.23	model 2I	5.25	5.26	model 2E
11	8.94	8.84	model 2I	8.80	8.62	model 2I
1	7.45	7.44	model 2I	7.42	7.43	model 2E
9	7.50	7.54	model 2E	7.54	7.57	model 2E
17	8.09	8.12	model 2E	8.15	8.17	model 2E
20	7.73	7.69	model 2I	7.33	7.58	model 2E

Tables 6A.3, 6A.4 and 6A.5 show the estimation results of models 1, 2E and 3E, respectively, for the osteoarthritis-rheumatoid-arthritis category.

Table 6A.3.
Estimation results of model 1 -osteoarthritis-rheumatoid-arthritis-.

Brand code	Trial rate: External influence $\hat{\beta}_{10i}$	Trial rate: Internal influence $\hat{\beta}_{2i}$	Repeat rate $\hat{\beta}_{3i}$	Average market share (in units)	MAD	MAPE	r
3	-0.06^{***}	2.01^{***}	0.06^{***}	0.03	54.87	16.39	0.82
12		0.63^{**}	0.13^{***}	0.10	88.11	9.34	0.93
13	-0.01^{***}	1.83^{***}	0.02^{***}	0.01	23.69	20.81	0.92
4	-0.02^{*}	1.75^{***}	0.02^{***}	0.03	34.60	14.44	0.63
11	0.002^{o}	1.17^{***}		0.01	4.82	4.72	0.96
5	0.01^{***}	0.76^{***}	0.01^{*}	0.02	3.87	2.30	0.89
1	0.01^{***}	1.08^{***}		0.02	3.58	1.74	0.98
2	0.08^{***}	0.30^{*}	0.19^{***}	0.17	18.95	1.18	0.95
19	0.02^{***}	0.56^{***}	0.20^{***}	0.12	6.21	0.53	0.99

***: $p \leq 0.0001$; **: $p \leq 0.001$; *: $p \leq 0.05$; ^{o}: $p<0.1$

Table 6A.4.
Estimation results of model 2E -osteoarthritis-rheumatoid-arthritis-.

Brand code	Trial rate: External influence $\hat{\beta}_{10i}$	Trial rate: External influence $\hat{\beta}_{11i}$	Trial rate: Internal influence $\hat{\beta}_{2i}$	Repeat rate $\hat{\beta}_{3i}$	Average market share (in units)	MAD	MAPE	r
3	0.04^{***}	0.01^{***}	1.23^{***}	0.06^{*}	0.03	50.15	14.98	0.86
12	0.08^{***}	0.01^{***}		0.14^{***}	0.10	65.97	7.00	0.93
13	0.02^{***}		1.80^{***}		0.01	23.76	20.87	0.92
4	0.05^{***}	-0.002^{*}	1.86^{***}	0.02^{***}	0.03	35.14	14.67	0.60
11	0.02^{***}	-0.001^{o}	1.20^{***}	0.001^{***}	0.01	4.65	4.55	0.96
5	0.02^{***}		0.77^{***}	0.01^{***}	0.02	3.75	2.23	0.89
1	0.03^{***}		1.08^{***}	0.01^{***}	0.02	3.56	1.73	0.98
2	0.11^{***}	0.07^{**}		0.19^{***}	0.17	14.32	0.89	0.97
19	0.08^{***}		0.48^{***}	0.20^{***}	0.12	5.22	0.44	0.99

***: $p \leq 0.0001$; **: $p \leq 0.001$; *: $p \leq 0.05$; ^{o}: $p<0.1$

Table 6A.5.
Estimation results of model 3E -osteoarthritis-rheumatoid-arthritis-.

Brand code	Trial rate: External influence $\hat{\beta}_{10i}$	$\hat{\beta}_{11i}$	$\hat{\beta}_{11ci}$	Internal influence $\hat{\beta}_{2i}$	Repeat rate $\hat{\beta}_{3i}$	Average market share (in units)	MAD	MAPE	r
3	0.04^{***}		-0.05^{***}	0.89^{***}	0.06^{***}	0.03	38.96	11.63	0.92
12	0.13^{***}		-0.13^{***}	0.80^{***}	0.14^{***}	0.10	44.00	4.67	0.96
13	0.02^{***}	0.001^{*}	0.02^{**}	1.91^{***}	0.02^{***}	0.01	20.63	18.12	0.93
4	0.03^{***}		-0.03^{***}	1.21^{***}	0.03^{***}	0.03	18.61	7.77	0.88
11	0.02^{***}		-0.003^{***}	0.99^{***}	0.01^{**}	0.01	3.40	3.33	0.98
5	0.02^{***}		-0.003^{***}	0.55^{***}	0.02^{***}	0.02	2.91	1.73	0.93
1	0.03^{***}	-0.003^{*}	-0.003^{*}	1.05^{***}	0.01^{**}	0.02	3.65	1.77	0.98
2	0.11^{***}	0.05^{*}	-0.02^{o}		0.20^{***}	0.17	14.18	0.88	0.98
19	0.08^{***}			0.47^{***}	0.20^{***}	0.12	5.09	0.43	0.99

***: $p \leq 0.0001$; **: $p \leq 0.001$; *: $p \leq 0.05$; ^{o}: $p<0.1$

Tables 6A.6, 6A.7 and 6A.8 show the estimation results of models 1, 2E and 3E, respectively, for the asthma category.

Table 6A.6.
Estimation results of model 1 -asthma-.

Brand code	Trial rate: External influence $\hat{\beta}_{10i}$	Trial rate: Internal influence $\hat{\beta}_{10i}$	Repeat rate $\hat{\beta}_{10i}$	Average market share (in units)	MAD	MAPE	r
26	0.01^{***}	0.29^{*}	0.01^{***}	0.02	5.69	11.11	0.84
18	0.02^{***}	0.32^{***}	0.07^{***}	0.04	8.20	2.33	0.99
10		1.09^{***}	0.01^{***}	0.01	4.51	5.23	0.93
3	0.09^{***}	0.26^{***}	0.29^{***}	0.24	19.31	1.01	0.99
13	0.001^{**}	0.82^{***}	0.02^{***}	0.01	1.17	1.34	0.99
11	0.003^{o}		0.48^{***}	0.05	7.07	1.86	0.99
1	0.003^{*}	0.99^{***}	0.02^{***}	0.02	3.30	1.87	0.98
9	0.004^{***}	0.60^{***}	0.06^{***}	0.03	3.29	1.27	0.99
17	0.002^{*}	0.47^{*}	0.03^{*}	0.01	3.42	6.75	0.85
20	0.01^{***}	0.20^{**}	0.18^{***}	0.06	2.99	0.67	0.99

***: $p \leq 0.0001$; **: $p \leq 0.001$; *: $p \leq 0.05$; ^{o}: $p<0.1$

Table 6A.7.
Estimation results of model 2E -asthma-.

Brand code	Trial rate			Repeat rate	Average market share (in units)	MAD	MAPE	r
	External influence		Internal influence					
	$\hat{\beta}_{10i}$	$\hat{\beta}_{11i}$	$\hat{\beta}_{2i}$	$\hat{\beta}_{3i}$				
26	0.01^{***}	0.001^{*}		0.02^{***}	0.02	5.38	10.51	0.86
18	0.03^{***}	0.003^{***}	0.32^{***}	0.07^{***}	0.04	7.39	2.10	0.99
10	0.01^{***}		1.07^{***}	0.01^{***}	0.01	4.55	5.28	0.93
3	0.16^{***}		0.25^{***}	0.29^{***}	0.24	19.46	1.02	0.99
13	0.01^{***}		0.81^{***}	0.02^{***}	0.01	1.17	1.33	0.99
11				0.64^{**}	0.05	6.48	1.70	0.99
1	0.03^{***}		0.97^{***}		0.02	3.23	1.82	0.98
9	0.02^{***}		0.55^{***}	0.06^{***}	0.03	3.04	1.17	0.99
17	0.01^{***}		0.44^{*}	0.03^{*}	0.01	3.29	6.49	0.85
20	0.02^{***}		0.25^{***}	0.17^{***}	0.06	2.96	0.66	0.99

***: $p \leq 0.0001$; **: $p \leq 0.001$; *: $p \leq 0.05$

Table 6A.8.
Estimation results of model 3E -asthma-.

Brand code	Trial rate				Repeat rate	Average market share (in units)	MAD	MAPE	r
	External influence			Internal influence					
	$\hat{\beta}_{10i}$	$\hat{\beta}_{11i}$	$\hat{\beta}_{11ci}$	$\hat{\beta}_{2i}$	$\hat{\beta}_{3i}$				
26	0.004^{***}	0.001^{**}	-0.002^{*}		0.03^{***}	0.02	4.85	9.47	0.89
18	0.03^{***}	0.003^{***}		0.32^{***}	0.07^{***}	0.04	7.42	2.11	0.99
10	0.02^{***}		0.002^{*}	1.12^{***}	0.01^{***}	0.01	4.29	4.97	0.93
3	0.18^{***}		0.04^{*}	0.22^{**}	0.28^{***}	0.24	19.53	1.02	0.99
13	0.01^{***}			0.79^{***}	0.02^{***}	0.01	1.20	1.36	0.99
11		0.003^{*}	-0.01^{*}		0.28^{***}	0.05	7.10	1.87	0.99
1	0.03^{***}			0.96^{***}	0.02^{***}	0.02	3.19	1.80	0.98
9	0.02^{***}			0.56^{***}	0.06^{***}	0.03	3.05	1.18	0.99
17	0.01^{***}			0.44^{*}	0.03^{*}	0.01	3.28	6.48	0.85
20	0.02^{***}	0.003^{**}	-0.01^{**}	0.20^{**}	0.18^{***}	0.06	2.33	0.52	0.99

***: $p \leq 0.0001$; **: $p \leq 0.001$; *: $p \leq 0.05$

Tables 6A.9 and 6A.10 show the results of the likelihood ratio tests for osteoarthritis-rheumatoid-arthritis and asthma, respectively.

Table 6A.9.
Likelihood ratio tests -osteoarthritis-rheumatoid-arthritis-.

Brand code	Restricted model: model 1 Unrestricted model: model 2E χ^2	Retained model	Restricted model: model 1 Unrestricted model: model 3E χ^2	Retained model	Restricted model: model 2E Unrestricted model: model 3E χ^2	Retained model
3	24.98*	model 2E	85.47*	model 3E	60.48*	model 3E
12	37.94*	model 2E	111.75*	model 3E	73.81*	model 3E
13	0.04	model 1	19.61*	model 3E	19.56*	model 3E
4	2.66	model 1	75.78*	model 3E	78.45*	model 3E
11	1.88	model 1	48.25*	model 3E	46.37*	model 3E
5	0.00	model 1	23.21*	model 3E	23.21*	model 3E
1	2.26	model 1	7.30*	model 3E	5.03*	model 3E
2	12.80*	model 2E	16.49*	model 3E	3.69^o	model 3E
19	2.62	model 1	5.23^o	model 3E	2.61	model 2E

*: Significant at 0.05 level; ^{o}: Significant at 0.1 level.

Table 6A.10.
Likelihood ratio tests -asthma-.

Brand code	Restricted model: model 1 Unrestricted model: model 2E χ^2	Retained model	Restricted model: model 1 Unrestricted model: model 3E χ^2	Retained model	Restricted model: model 2E Unrestricted model: model 3E χ^2	Retained model
26	11.00*	model 2E	26.47*	model 3E	15.47*	model 3E
18	23.92*	model 2E	24.23*	model 3E	0.31	model 2E
10	1.85	model 1	6.21*	model 3E	4.37*	model 3E
3	0.83	model 1	5.69^o	model 3E	4.86*	model 3E
13	0.03	model 1	1.06	model 1	1.03	model 2E
11	0.14	model 1	9.59*	model 3E	9.73*	model 3E
1	0.48	model 1	3.55	model 1	3.08^o	model 3E
9	2.95^o	model 2E	3.08	model 1	0.13	model 2E
17	1.05	model 1	1.05	model 1	0.002	model 2E
20	2.12	model 1	17.66*	model 3E	15.55*	model 3E

*: Significant at 0.05 level; ^{o}: Significant at 0.1 level.

Appendix 6B. Some results from the recursive window approach

Figures 6B.1 to 6B.4 show, for some drugs in the rhinitis category, the following plots:

i) in the first line: the temporal pattern of the mean level of expenditures on detailing, medical journal advertising, physician meetings and direct-to-consumer advertising,
ii) in the first column: the temporal pattern of the estimates of the time-varying diffusion parameters -the basic propensity to try ($\hat{\beta}_{10i,t}$), the internal influence coefficient ($\hat{\beta}_{2i,t}$) and the repeat rate ($\hat{\beta}_{3i,t}$)-, and
iii) in the other lines and columns: the scatter plots of the estimates of the time-varying diffusion parameters and the mean level of expenditures on each marketing instrument.

Figures 6B.5 to 6B.10 show, for some drugs in the rhinitis category, the following plots:

i) in the first line: the temporal pattern of the mean level of expenditures on direct-to-consumer advertising, direct-to-physician marketing and aggregate marketing,
ii) in the first column: the temporal pattern of the estimates of the time-varying diffusion parameters -the basic propensity to try ($\hat{\beta}_{10i,t}$), the internal influence coefficient ($\hat{\beta}_{2i,t}$) and the repeat rate ($\hat{\beta}_{3i,t}$)-, and
iii) in the other lines and columns: the scatter plots of the estimates of the time-varying diffusion parameters and the mean level of expenditures on each marketing instrument.

In general terms, we show that $\hat{\beta}_{10i,t}$ and $\hat{\beta}_{3i,t}$ follow the same temporal tendency as the mean level of expenditures on detailing, direct-to-physician marketing and aggregate marketing. This is not the common pattern for the other marketing instruments. This seems to indicate that detailing expenditures are relevant in determining the temporal tendency of these diffusion parameters. However, $\hat{\beta}_{2i,t}$ follows the opposite pattern to $\hat{\beta}_{10i,t}$ and $\hat{\beta}_{3i,t}$. Table 6B.1 summarizes these results.

Table 6B.1
Temporal patterns of the time-varying diffusion parameters and the mean of the log of expenditures on the marketing instruments

	Brand 1	Brand 4	Brand 9	Brand 12
$\hat{\beta}_{10i,t}$	increasing	almost constant with a slight decreasing tendency	decreasing at the beginning and increasing at the end	decreasing at the beginning and increasing at the end
$\hat{\beta}_{2i,t}$	decreasing	almost constant with a slight increasing tendency	increasing at the beginning and decreasing at the end	increasing at the beginning and decreasing at the end
$\hat{\beta}_{3i,t}$	increasing	decreasing	decreasing at the beginning and increasing at the end	decreasing at the beginning and increasing at the end
Average log detailing expenditures	slight increasing tendency	decreasing	slight increasing tendency	slight increasing tendency
Average log medical journal advertising expenditures	decreasing at the beginning and increasing at the end	decreasing	decreasing at the beginning with a slight increase at the end	decreasing
Average log physician meetings Expenditures	increasing	decreasing	decreasing at the beginning and increasing at the end	slight increasing tendency
Average log direct-to-consumer advertising expenditures	slight increasing tendency	increasing at the beginning and then decreasing	increasing	increasing
Average log direct-to-physician marketing expenditures	slight increasing tendency	decreasing	decreasing	decreasing with a slight increase at the end
Average log marketing expenditures	increasing	decreasing	slight decreasing tendency	increasing

Table 6B.2 summaries the results from the scatter plots and shows the correlation coefficients with the level of significance. In general terms, these results show a positive and significant correlation between $\hat{\beta}_{10i,t}$ and the mean level of expenditures on detailing, physician meetings, direct-to-physician marketing and aggregate marketing. This reveals that high values of $\hat{\beta}_{10i,t}$ are related to high levels of expenditures on direct-to-physician marketing, particularly on detailing and physician meetings. There is not a clear pattern for medical journal advertising nor direct-to-consumer advertising. The results show the same pattern for $\hat{\beta}_{3i,t}$ but the opposite for $\hat{\beta}_{2i,t}$.

Table 6B.2
Correlation between the time-varying diffusion parameters and the mean level of expenditures on the marketing instruments

	Average log detailing expenditures	Average log medical journal adv. expenditures	Average log physician meetings expenditures	Average log direct-to-consumer advertising expenditures	Average log direct-to-physician marketing expenditures	Average log marketing expenditures
Brand 1						
$\hat{\beta}_{10i,t}$	0.95***	0.52**	0.91***	0.78***	0.93***	0.91***
$\hat{\beta}_{2i,t}$	-0.94***	-0.52**	-0.88***	-0.78***	-0.91***	-0.90***
$\hat{\beta}_{3i,t}$	0.88***	0.50*	0.82***	0.74***	0.85***	0.85***
Brand 4						
$\hat{\beta}_{10i,t}$	0.76***	0.71***	0.62***	0.44**	0.73***	0.71***
$\hat{\beta}_{2i,t}$	-0.91***	-0.94***	-0.86***	-0.49**	-0.92***	-0.88***
$\hat{\beta}_{3i,t}$	0.78***	0.89***	0.77***	0.26^{o}	0.84***	0.75***
Brand 9						
$\hat{\beta}_{10i,t}$	0.35*	0.84***	0.39*	-0.71***	0.88***	0.88***
$\hat{\beta}_{2i,t}$	-0.72***	0.21	-0.64***	-0.20	0.05	-0.05
$\hat{\beta}_{3i,t}$	0.54***	0.05	0.73***	-0.08	0.22^{o}	0.28*
Brand 12						
$\hat{\beta}_{10i,t}$	0.82***	-0.77***	0.79***	0.77***	-0.50***	0.68**
$\hat{\beta}_{2i,t}$	-0.80***	0.77***	-0.78***	-0.76***	0.51*	-0.67**
$\hat{\beta}_{3i,t}$	0.76***	-0.76***	0.74***	0.74***	-0.53*	0.63**

***: $p \leq 0.0001$; **: $p \leq 0.001$; *: $p \leq 0.05$; ^{o}: $p<0.1$

Figure 6B.1. Time-varying diffusion parameters –basic propensity to try ($\beta_{10i,t}$), internal influence ($\beta_{2i,t}$) and repeat rate ($\beta_{3i,t}$)- and the mean of the log of expenditures on detailing (DTL), medical journal advertising (JAD), physician meetings (MTG) and direct-to-consumer advertising (DTC). [Drug No 1 – rhinitis category]

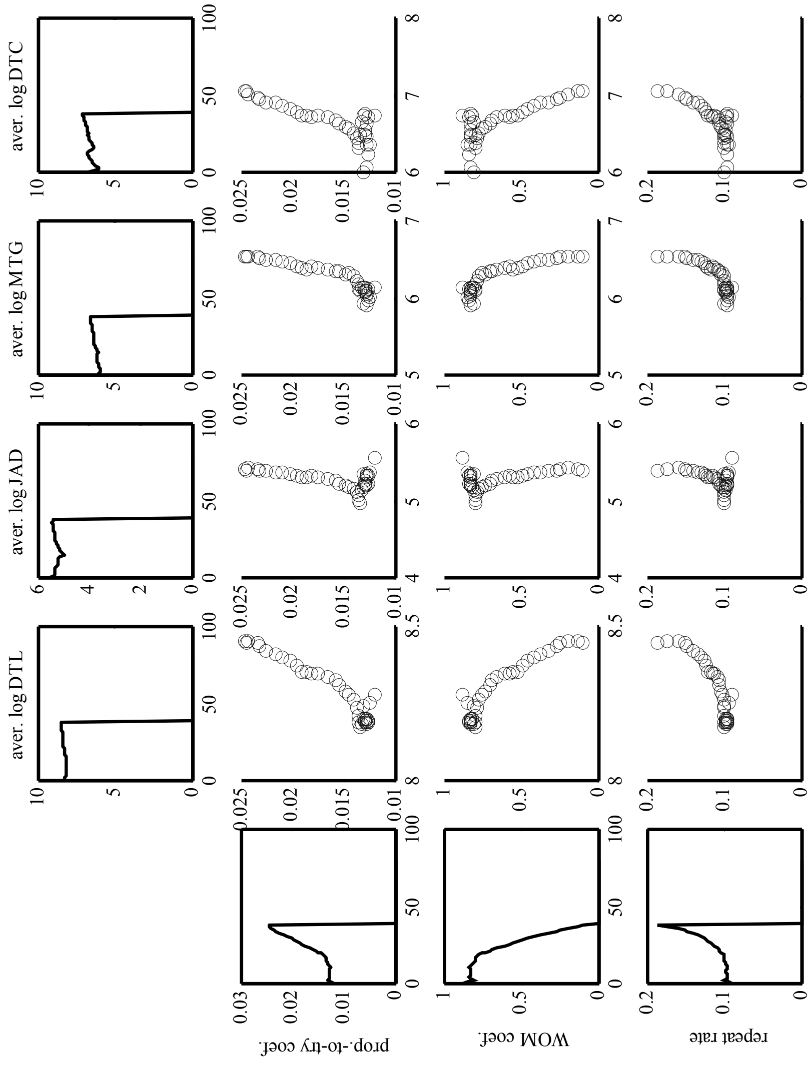


Figure 6B.2. Time-varying diffusion parameters –basic propensity to try ($\beta_{10i,t}$), internal influence ($\beta_{2i,t}$) and repeat rate ($\beta_{3i,t}$)- and the mean of the log of expenditures on detailing (DTL), medical journal advertising (JAD), physician meetings (MTG) and direct-to-consumer advertising (DTC). [Drug No 4 – rhinitis category]

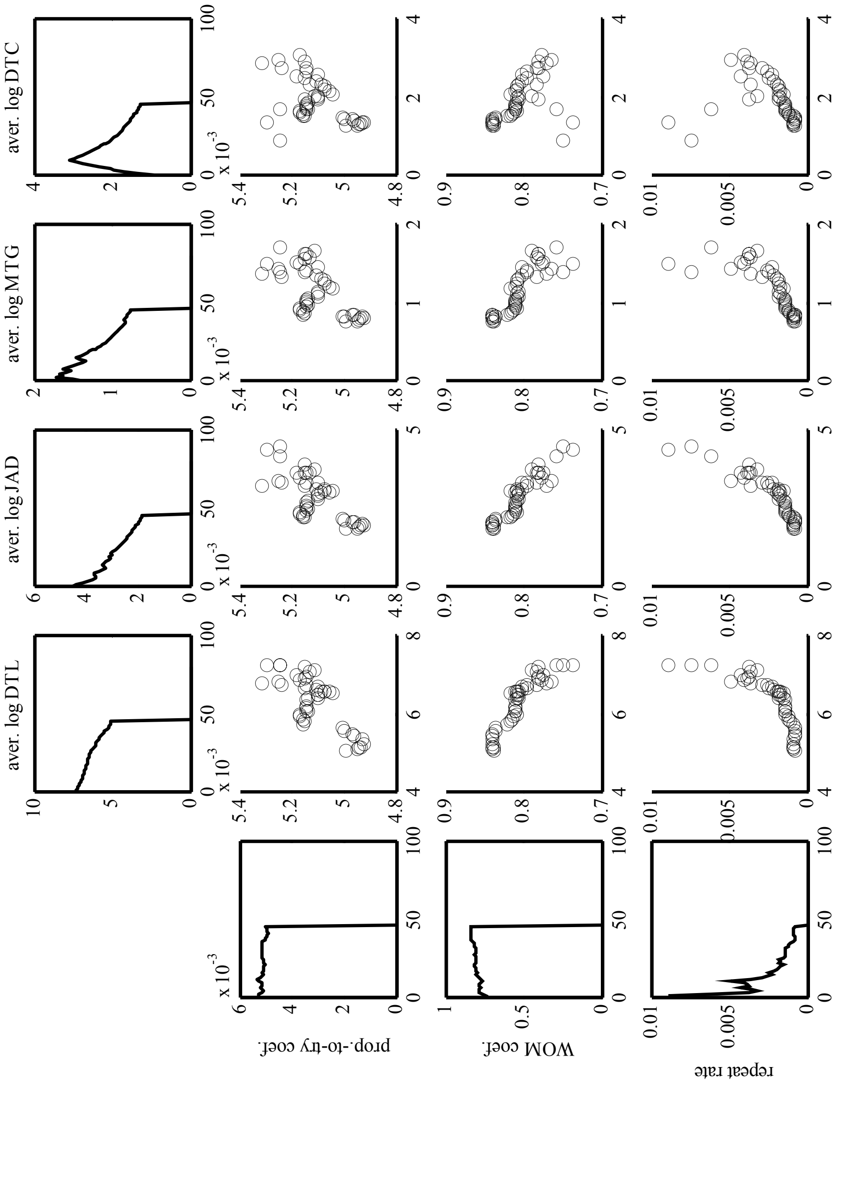


Figure 6B.3. Time-varying diffusion parameters –basic propensity to try ($\beta_{10i,t}$), internal influence ($\beta_{2i,t}$) and repeat rate ($\beta_{3i,t}$)- and the mean of the log of expenditures on detailing (DTL), medical journal advertising (JAD), physician meetings (MTG) and direct-to-consumer advertising (DTC). [Drug No 9 – rhinitis category]

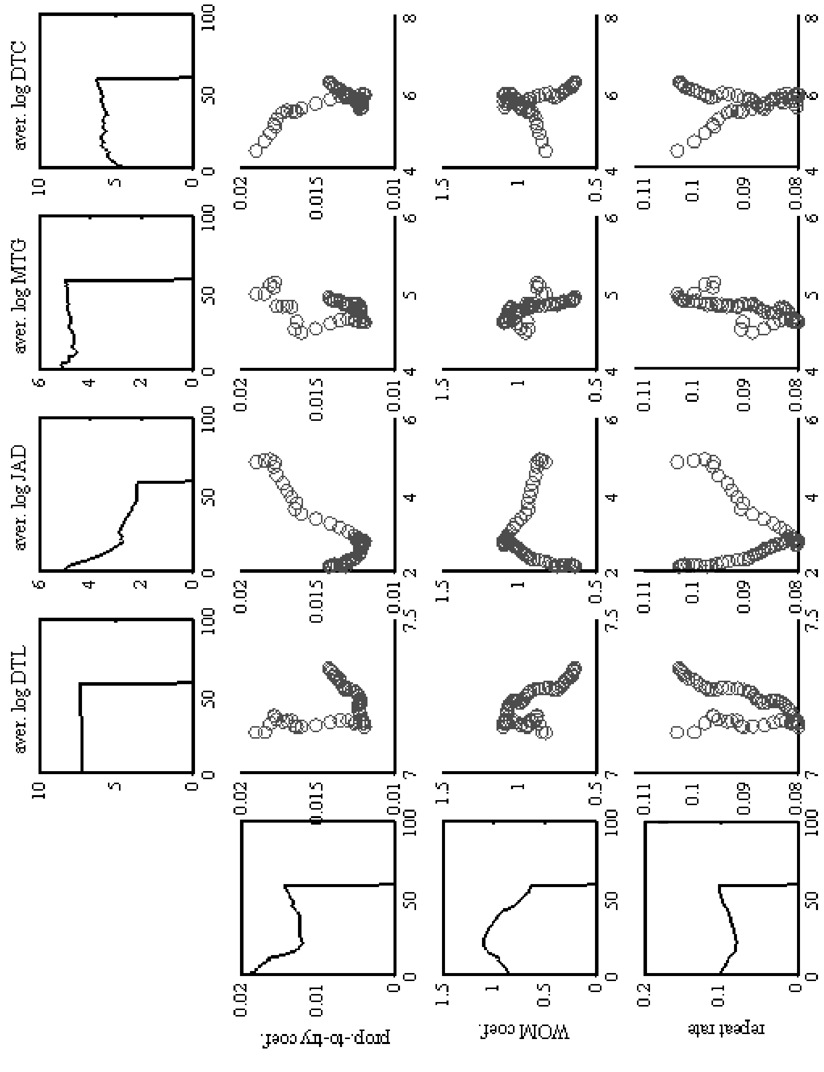


Figure 6B.4. Time-varying diffusion parameters –basic propensity to try ($\beta_{10i,t}$), internal influence ($\beta_{2i,t}$) and repeat rate ($\beta_{3i,t}$)- and the mean of the log of expenditures on detailing (DTL), medical journal advertising (JAD), physician meetings (MTG) and direct-to-consumer advertising (DTC). [Drug No 12 – rhinitis category]

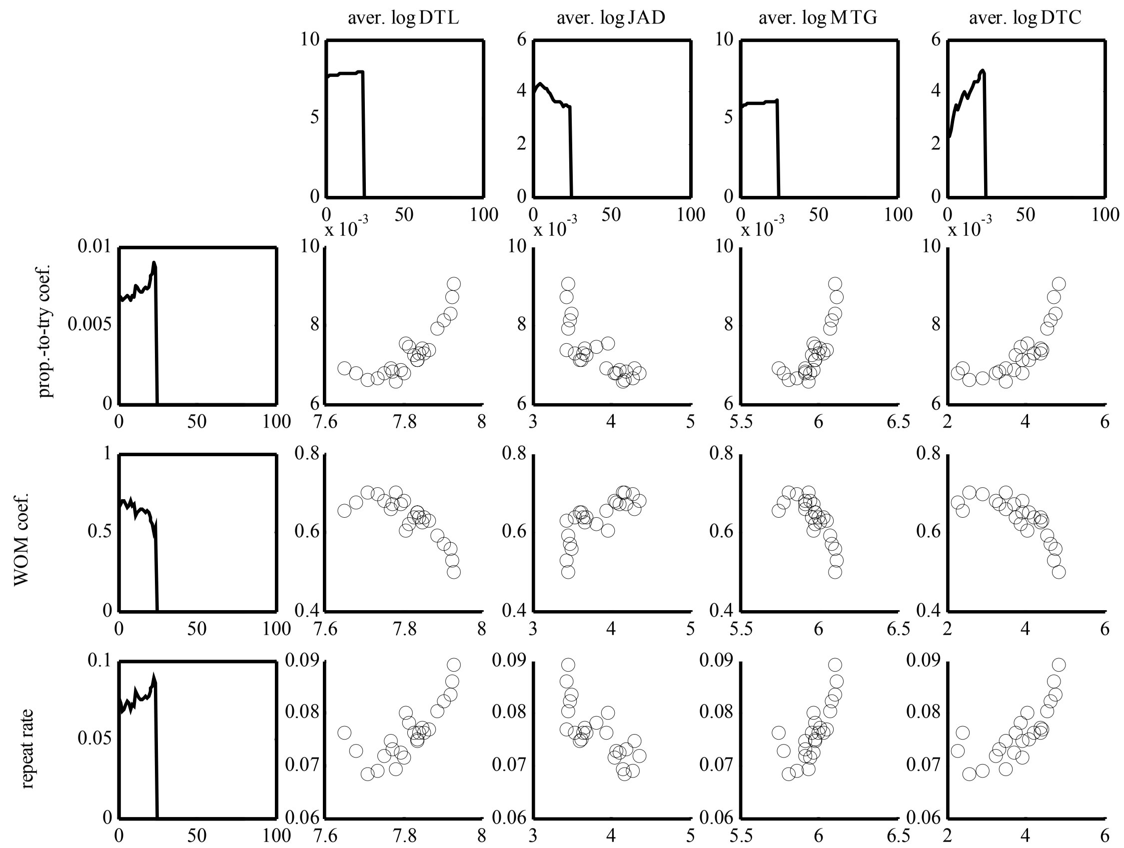


Figure 6B.5. Time-varying diffusion parameters –basic propensity to try ($\beta_{10i,t}$), internal influence ($\beta_{2i,t}$) and repeat rate ($\beta_{3i,t}$)- and the mean of the log of expenditures on direct-to-consumer advertising (DTC), direct-to-physician marketing (DTP) and aggregated marketing (MK). [Drug No 1 – rhinitis category]

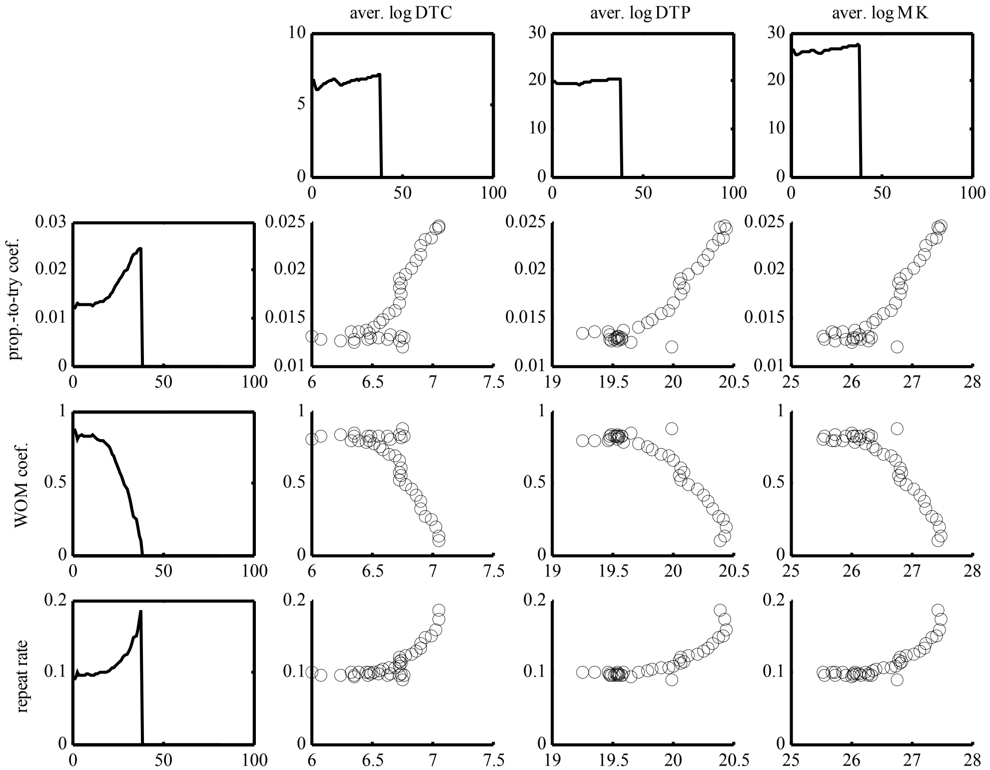


Figure 6B.6. Time-varying diffusion parameters –basic propensity to try ($\beta_{10i,t}$), internal influence ($\beta_{2i,t}$) and repeat rate ($\beta_{3i,t}$)- and the mean of the log of expenditures on direct-to-consumer advertising (DTC), direct-to-physician marketing (DTP) and aggregated marketing (MK). [Drug No 4 – rhinitis category]

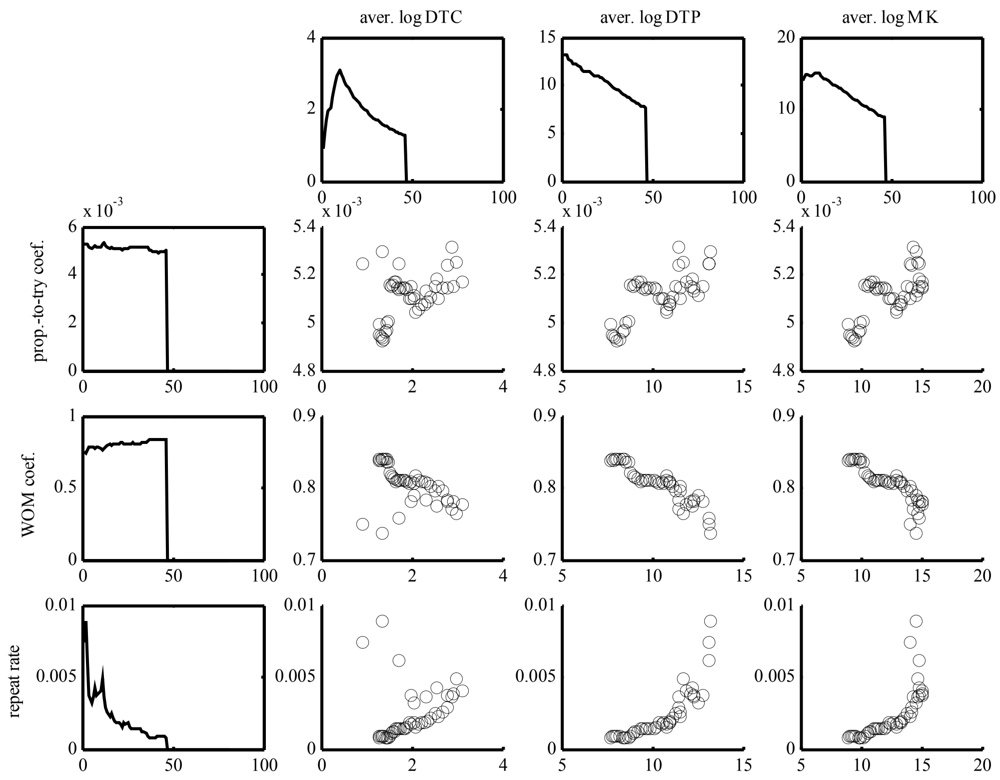


Figure 6B.7. Time-varying diffusion parameters –basic propensity to try ($\beta_{10i,t}$), internal influence ($\beta_{2i,t}$) and repeat rate ($\beta_{3i,t}$)- and the mean of the log of expenditures on direct-to-consumer advertising (DTC), direct-to-physician marketing (DTP) and aggregated marketing (MK). [Drug No 9 – rhinitis category]

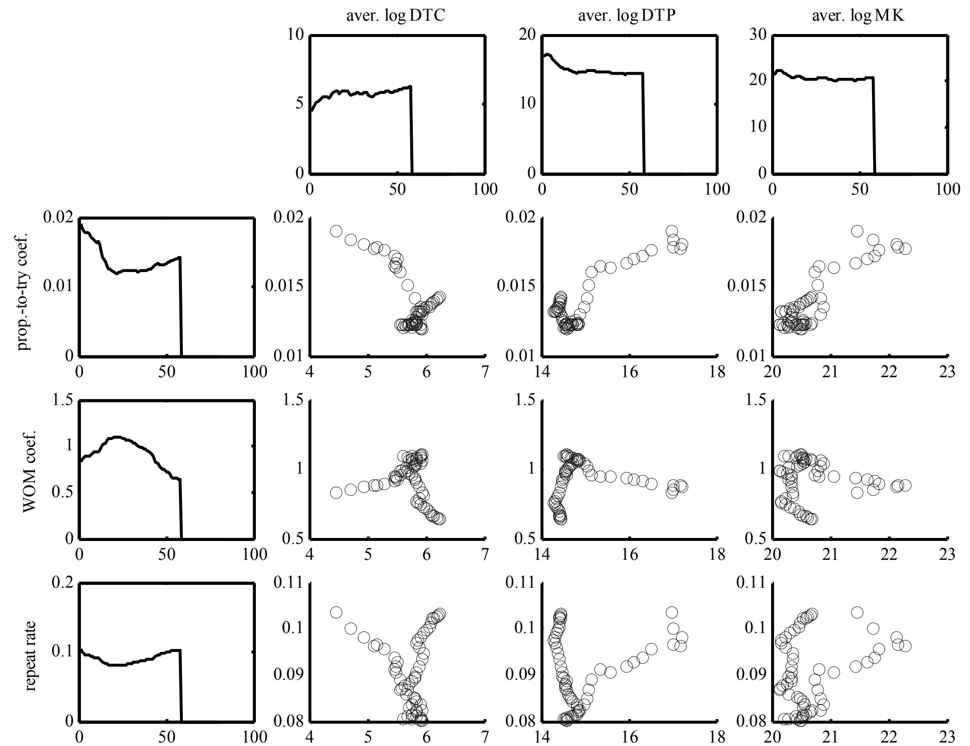
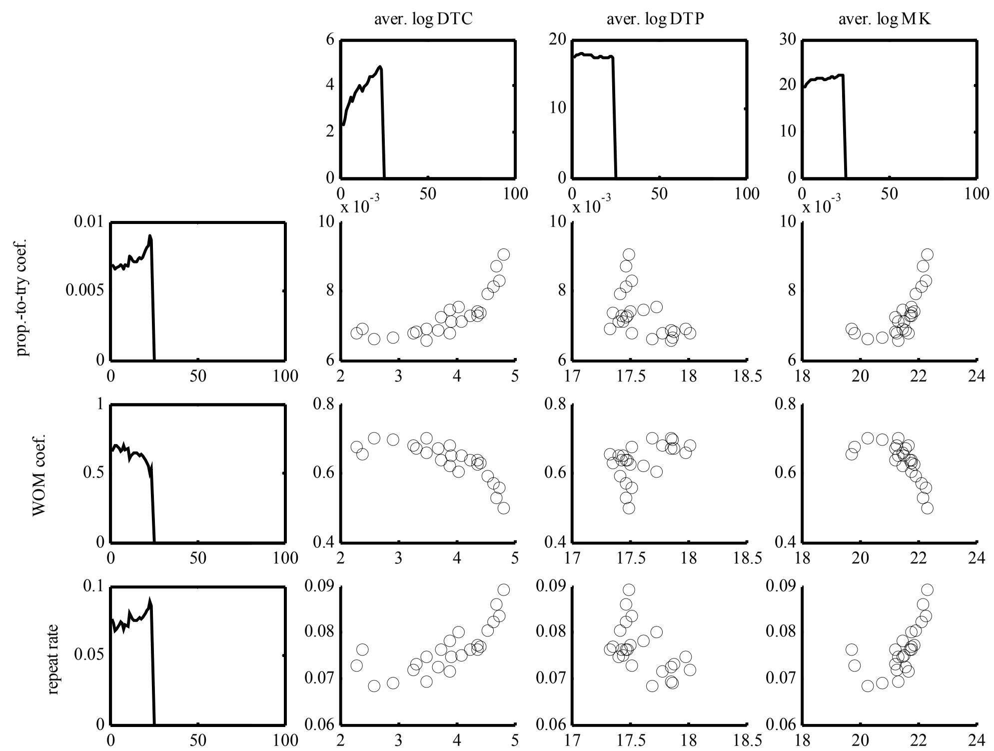


Figure 6B.8. Time-varying diffusion parameters –basic propensity to try ($\beta_{10i,t}$), internal influence ($\beta_{2i,t}$) and repeat rate ($\beta_{3i,t}$)- and the mean of the log of expenditures on direct-to-consumer advertising (DTC), direct-to-physician marketing (DTP) and aggregated marketing (MK). [Drug No 12 – rhinitis category]



Chapter 7

Summary and discussion

Firms make continuous improvements and renewals of their products. New products have to be developed, tested and successfully introduced into markets with intense competition. This is one of the major tasks of innovation management. Given the complexity, risk and highly dynamic nature of this kind of work, managers need the right tools to adequately develop their work. Diffusion models provide an important instrument to understand the dynamics of the diffusion process of innovations. Since the seminal work by Bass (1969), diffusion models have played an important role in marketing science for more than three decades, and research into diffusion modeling continues to be an active area of study. Many studies have been developed with a focus on different products, countries and situations.

Our aim in this thesis is to contribute to the methodological and substantive evolution of diffusion models by relaxing a number of restrictions of the classical diffusion models so that their application potential is increased.

We develop a review of the theoretical and empirical background of diffusion models in marketing (Chapter 2). We evaluate the body of research on diffusion modeling and discuss models that relax the assumptions -limitations- of the classical diffusion models:

- Assumption 1. The diffusion process is a binary process and population is homogeneous.
- Assumption 2. The population of adopters does not vary.
- Assumption 3. The parameters of external and internal influence do not change.
- Assumption 4. Only one adoption per adopter is permitted.
- Assumption 5. Geographical frontiers do not alter.
- Assumption 6. The innovation is diffused in isolation.
- Assumption 7. The characteristics of an innovation and its perception do not change.

Assumption 8. There are no supply restrictions.
Assumption 9. The impact of marketing strategies is implicitly captured by the model parameters.

A number of summary-tables have been included after identifying some key dimensions, which are used to characterize the models. The diffusion of innovations over time is a highly dynamic and complex problem. The classical or traditional diffusion models of innovations lack important details and Chapter 2 shows how these models can be extended to incorporate additional elements. We discuss a considerable number of diffusion models that relax the nine restrictive assumptions inherent in the traditional models. The extended diffusion models represent an important improvement in the understanding of the structure and forces driving the diffusion process of innovations.

In the subsequent chapters, we discuss specific extensions of the classical diffusion models and apply them to different contexts. In Chapter 3, we introduce the empirical applications we carry out on the diffusion of movies in Spain, France and Italy (Chapter 4), on the diffusion of franchising in Spain (Chapter 5) and on the diffusion of prescription drugs in the United States of America (Chapter 6). In Chapters 4 through 6, we develop extended diffusion models that overcome specific limitations of the classical models and hence allow for more realism in the modeling of the diffusion of innovations.

Although many normative diffusion models have been proposed in the literature, there is relatively little empirical work (Chatterjee, Eliashberg and Rao, 2000) that has attempted to validate the model specifications assumed by normative researchers. Parker and Gatignon (1994) provide a start in the descriptive validation of diffusion model specifications to enhance the relevance and value of the normative models. Their study shows that asymmetries in the diffusion process exist across the brands in the category of products they analyze. This implies that normative models, which are usually employed by the Bass model as the demand model, should recognize these asymmetries in order to provide appropriate optimal marketing strategies. We have followed this direction by developing three empirical applications. The models we present are descriptive and do not incorporate normative factors, such as the optimal launch time for each product or the optimal time for a product to enter or leave the market.

In the remainder of this chapter, we present the conclusions and contributions of our study and discuss limitations and directions for future research.

Diffusion of movies in neighboring Mediterranean countries (Chapter 4)

This research focuses on marketing decision variables and introductions into different markets, two of the multiple concerns that managers have regarding the diffusion process of innovations. Although research on price and advertising is extensive in diffusion modeling, distribution is rarely incorporated. Scarce availability of data on this decision variable is mainly responsible for the current state of affairs. This research contributes to modeling literature on new product diffusion models by extending the models proposed by Jain and Rao (1990) and Bass, Krishnan and Jain (1994) to explicitly incorporate distribution. Researchers believe that both the socio-economic environment and time lags in introducing new products into the market are relevant factors in explaining differences among the diffusion processes of the same product in different geographical areas. Hence, this study also adds to the literature on international diffusion by analyzing the importance of the *country* and *time effects* to give a better understanding of the differences in diffusion patterns between countries that are geographically close. These questions have motivated us to analyze these phenomena in the context of the diffusion of movies, in three Mediterranean European countries -Spain, France and Italy-, based on data for the period 1997-1999. Thus, the empirical application extends the use of Bass-type diffusion models to products other than the classical consumer durables, i.e. to entertainment and experience products. The model framework proposed in the Spanish context is extended to other settings: France and Italy.

Main results and conclusions

We demonstrate that there is no single common model that describes the diffusion patterns in all the analyzed markets. However, in general terms, the Generalized Bass model that accommodates the effects of distribution turns out to be as the preferred model. Results show that the diffusion processes of the analyzed movies are largely determined by three factors: two clear trigger factors are internal knowledge that consumers have about the movies (assumed through advertising, critic reviews or their innate innovativeness) and word-of-mouth interactions (assumed through social contagion among friends, colleagues or other close people who have already seen the movie), with another possible factor being the intensity distribution of the movie in the country concerned.

We also found a *country effect*, i.e. there are significant differences in revealed preferences between Spain and France and between Italy and France, although not between Spain and Italy. The cultural, economic, social or other differences between Spain and Italy do not seem to be large enough to provoke a significant difference between their diffusion processes. In this sense, these findings reinforce existing knowledge in the area, which points out the importance of country characteristics in the commercialization of innovations. However, whereas the *country effect* seems to be one reason for differences in the diffusion processes of the selected movies between some of the three countries, the *time effect* appears not to play an important role. We could not detect lead and lag patterns that suggest "sprinkler" strategies of introduction. One possible reason for this result is that as the differences in time between the moments of entrance of the movies in each country are very small, it is not easy to detect any effect on the diffusion processes.

Assumptions relaxed

As we pointed out in Chapter 3, the study discussed in Chapter 4 relaxes three of the nine limitations -assumptions 2, 3 and 9- of the Bass model. First, we allow the potential market to be dynamic; in our model we allow distribution to affect the size of the potential market (assumption 2). Second, we allow the parameters of external and internal influence to vary over the diffusion process of the innovation; more explicitly: we assume that distribution affects the adoption rate (assumption 3). And third, we explicitly consider a marketing variable: distribution (assumption 9).

Limitations and future research

Apart from the other assumptions pointed out in Chapter 2, which we do not relax (Table 2B in Appendix 2B shows that none of the extended diffusion models relax all nine assumptions and most relax just one or two), this study identifies other limitations that deserve consideration in future research. First, even though distribution has long been recognized as a relevant variable in a product's commercialization process, our results show distribution to be a weakly significant factor affecting the diffusion processes in the three analyzed countries. However, other possible ways of measuring and incorporating this variable into the model need to be considered. Second, it would also be worthwhile to include advertising in the diffusion models to improve their use for planning purposes. In our case, weekly data on advertising expenditures for each movie in the three analyzed countries are not available. Third, although this study reveals differences in the diffusion processes of movies in different geographical areas, it is helpful for managers to know the specific factors that account for this country effect. Specifically, this requires a second analysis to detect which social, economic, political, demographic and/or cultural factors affect this country effect. This implies obtaining disaggregated data on adopters from the three Mediterranean countries that are not yet available. Fourth, our empirical application explores and gives insight into designing marketing strategies for the introduction of just one product category in three countries, which poses a clear limitation for generalizing the results. Hence, it would be valuable to extend the study to other categories and countries within the same observational period. Fifth, the nature of the new products analyzed -movies- obliges us to study short data series, as has been done, for example, by Jones and Ritz (1991).

Diffusion of franchising in Spain (Chapter 5)

Research on the application of new diffusion models to organizational innovations is very scarce and underdeveloped. Insights into whether and how diffusion theory can be applied to such an innovation diffusion context is much needed. This study fills this gap by focusing on an organizational innovation, namely franchising. We consider the diffusion of franchising by firms (inter-firm diffusion) in Spain during the period 1974-1999. The adoption of this system of commercialization has important consequences for the adopting organization (the franchisor). The organizational benefits of franchising contribute to improvements in management and distribution channels. Franchising is a mechanism that reduces the divergence of interest between the two parties (franchisor and franchisee), reducing agency problems and allowing the possibility of reaching common goals. We apply well-known diffusion models to detect how many firms are influenced by firms that have adopted the franchising concept ("imitators") and how many firms are not influenced by the timing of the adoption by other firms ("innovators"). We develop a four-step approach to select the most appropriate diffusion model. After visual analysis of the data, we test whether the adoption follows a purely random process or whether firms imitate the adoption of the franchising concept. In the second step, we re-examine the imitation hypothesis, i.e. the ratio of inter-firm diffusion is governed by imitative behavior between adopters and non-adopters. In the third step, we compare some nested and non-nested models and the final selection is based on parameter stability and predictive validation criteria (fourth step).

Main results and conclusions

Our results suggest that the long-run diffusion process of franchising in Spain is appropriately captured by several Bass-type diffusion models taken from a family of models. However, the traditional Bass model presents better properties in terms of parameter stability and predictive validity. Results show that the adoption of franchising in Spain is only slightly affected by external influence whereas Spanish franchisors present strong imitating behavior. This suggests that if the Spanish Government, Spanish Franchising associations or Spanish Franchising fairs want to stimulate the adoption of franchising among Spanish firms, external influence should be enhanced by marketing efforts. Additionally, the results show the suitability of the imitation hypothesis of the diffusion models to explain the diffusion process of franchising in Spain, which was questioned by Mahajan, Sharma and Bettis (1988) regarding organizational innovations.

Assumptions relaxed

We note that for this organizational innovation -franchising- the decision maker is not the consumer, but the firm. In this application, we relax the first three assumptions of the Bass model. We relax assumption 1 by allowing for a heterogeneous population of adopters through the incorporation of a new parameter into some of the models. We also allow the potential market to depend on the number of Spanish firms in the marketplace during the diffusion process of the innovation (assumption 2). And, assumption 3 is relaxed by having a non-uniform parameter of internal influence in some of the diffusion models.

Limitations and future research

Apart from other assumptions mentioned earlier that we do not relax, this study has an especially relevant limitation that affects the application setting in which the study is conducted. In this study we do not distinguish different industries or sectors. It would be informative to address that distinction. However, the appropriate data necessary to calibrate the models in different industries or sectors is not yet available. These limitations deserve attention in future research. Our results show that, among the proposed family of diffusion models, the traditional Bass-model (a diffusion model with a fixed potential market) shows better proprieties than those with a dynamic potential market. However, other possible ways of measuring and incorporating a dynamic potential market into the model need to be considered, especially when a distinction among different industries or sectors is incorporated. Furthermore, although this study represents a valuable starting point for the reexamination of organizational innovations with diffusion models, other useful studies for managers are those that answer questions such as:

- which of the characteristics of a franchising system have mainly favored its diffusion?, or
- what is the role played by the competitive environment in the diffusion of franchising?.

Diffusion of prescription drugs in the United States of America (Chapter 6)

In this research we employ diffusion modeling to investigate the longitudinal and cross-sectional effects of marketing expenditures on the diffusion of new prescription drugs from three product categories. Pharmaceutical marketing has been criticized as wasteful and excessive and for contributing to the overuse, misuse and misprescription of drugs. However, marketing also serves as a key communication channel for continuing physician education regarding pharmaceutical products and for exposing consumers to information that may improve health outcomes. We use a trial-repeat purchase diffusion model calibrated for each new drug introduced in the categories of rhinitis, osteoarthritis-rheumatoid-arthritis and asthma drugs in the US market within the period 1993-2000. We extend the model proposed by Hahn et al. (1994) to incorporate the effect of the company's and competitors' promotional efforts separately. In contrast to studies that either use aggregate measures for marketing expenditures or expenditures for a single instrument, our model accommodates heterogeneity in the effects of the different marketing instruments. Thus, our model allows for the analyses of the effects of marketing directed at physicians ("push" strategy) and direct-to-consumer advertising ("pull" strategy). Following existing literature, we assume that longitudinal marketing efforts affect the trial rate. We propose a family of trial-repeat diffusion models to determine whether marketing affects the trial rate either through external effects or via internal effects. We investigate the cross-sectional effects by performing a second-stage analysis on the estimated parameter of the diffusion model.

Main results and conclusions

We find support for the hypothesis that changes in own marketing expenditures are positively related to changes in the trial rate. We also find support for the hypothesis that the trial rate is negatively affected by competitors' marketing expenditures. The results indicate that each brand can follow a specific diffusion process and that the impact of marketing efforts can vary for each brand. However, in general terms, the external influence formulation is revealed as the most appropriate specification to incorporate marketing variables in the trial-repeat diffusion model for the three categories analyzed. Besides these longitudinal effects, we also find cross-sectional effects. We find that the mean level of marketing expenditures is positively related to the basic propensity to try the new product and to the repeat rate but apparently not related to internal influence. These results hold for all three drug categories analyzed, except in the case of rhinitis, where marketing expenditures are negatively related to internal influence. This implies that marketing expenditures have both an informative and persuasive influence on the diffusion of new pharmaceutical products.

The cross-sectional analysis also reveals insights into the order of entry of the new drugs in the market and the importance of branded versus generic drugs. Order of entry is found to play an important role in the launch strategy of the new products in the rhinitis category, which has only branded drugs. Branded drugs launched early seem to have a better opportunity of occupying a preferential position in the physicians' product space. However, when we consider the other categories, order of entry becomes less important. In this analysis we also find that for generics, there is a higher basic propensity to try, a larger effect of internal influence and a higher repeat rate than for branded drugs. Finally, the results of this study lead us to perform an in-depth analysis of the impact of the different marketing instruments on the time-varying diffusion parameters. We introduce a different approach -a recursive time window approach- and show some preliminary results for the rhinitis category. These results show that marketing efforts directed at physicians, especially detailing, but also physician meetings, are a key factor in determining the temporal pattern of the diffusion parameters. There seems to be no clear pattern for both medical journal advertising and direct-to-consumer advertising.

Assumptions relaxed

As we discussed in Chapter 3, in the study on prescription drugs -frequently purchased consumer products- the decision maker is not the consumer, but the doctor. In this application, four assumptions in the Bass model are relaxed. We relax assumption 3 by assuming that marketing variables affect external and/or internal influence over the diffusion process. We relax assumption 4 and incorporate repeat purchases into the diffusion model. We also consider the effect of competitive variables on the diffusion process (assumption 6) and we incorporate marketing variables, such as detailing, medical journal advertising, physician meetings and direct-to-consumer advertising (assumption 9).

Limitations and future research

Although the model proposed in this study relaxes some limitations of the earlier trial-repeat diffusion models making it more realistic, several simplifying assumptions of the models remain. First, the number of physicians in the product category is fixed. Second, all consumers are assumed to purchase a product in the product category in each period. However, Hahn et al. (1994) point out that relaxing this assumption adds considerable complexity to the model, and this is not a highly problematic assumption for monthly data. Additionaly, this assumption deals with the presence of an outside good, which allows for category expansion. Third, all the physicians are assumed to belong to the same class. Lilien, Rao and Kalish (1981) point out that this can be relaxed by constructing a series of parallel processes for each class of doctors. Fourth, the usage rate of the new products is the same as that of mature products. Fifth, the repeat rate is not affected by promotional efforts. Considering promotional efforts affecting both trial rate and repeat rate leads to econometric problems (multicollinearity). These limitations deserve attention in future research.

In conclusion, we point out the benefit of continued research pertaining to theoretical and empirical extensions of the diffusion models. Theoretical extensions may be directed towards the relaxation of the limitations identified in each of our studies and the assumptions presented in detail in Chapter 2.

The relaxation of assumptions may involve such appealing issues as the stochastic modeling of the diffusion process of innovations and modeling the adoption process at the micro-level, based on reasonable behavioral hypotheses. Empirical extensions may be directed towards examining other innovations to assess the generalizability of the results obtained in this thesis and in other studies; in particular, examining the way marketing decision variables affect diffusion model parameters and the shapes of these variables' functions. We focus our three empirical applications (Chapters 4, 5 and 6) on new products that have scarcely been studied in the literature of diffusion models. Most applications of diffusion models are on new durable consumer products, such as blenders, calculators, clothes dryers, dishwashers, disposers, freezers, irons, refrigerators, color and black and white TVs, whereas few applications are on other kinds of consumer products, non-durable products, services or organizational innovations. Future research on other categories of new products will enhance our understanding of how diffusion models work in different situations. As Chatterjee, Eliashberg and Rao (2000) suggest, the findings would indicate appropriate model specifications for normative research that could be used as an aid in developing suitable initial strategies for new products.

This thesis contributes to the stream of research on Bass-type diffusion models in which restrictions are relaxed in their specifications to allow the models to become more useful tools for managers in solving problems regarding innovation decisions in different situations (products and contexts). A better understanding of the dynamics of diffusion models and their applicability to managerial problems favor their usefulness. The present study has explored specific issues behind the diffusion process of innovations and therefore provides a better understanding of how to manage this process. Several managerial implications are identified.

Interpersonal communication (internal influence) is confirmed as the main driver in the diffusion process of different types of innovations: organizational forms (franchising), experience consumer products (movies) and frequently purchased consumer products (prescription drugs). Although non interpersonal communication (external influence) is also confirmed as a main driver for consumer innovations, when adopters are firms (such as in the case of franchising as an organizational innovation) external influence becomes less relevant. This could be caused by the higher risk inherent in the adoption of organizational innovations.

The managers of the motion picture industry should take into account the fact that both external and internal influences drive the diffusion process of movies in the analyzed European countries. However, they have to proceed with caution in the use of information on the diffusion process of movies in other countries, since the level of internal influence varies across countries, despite their geographical proximity. The idiosyncrasies of individual countries could lead to these differences. Additionally, managers should also take into account the fact that the number of screens where a movie is exhibited enhances its diffusion process, although modestly.

Although Bass-type diffusion models are traditionally not used for analyzing organizational innovations, our findings show the applicability of these models to the diffusion of franchising. In particular, the implantation of the franchising system in Spain is appropriately captured by three diffusion models: a diffusion model which considers only internal influence, a diffusion model which considers external and internal influence and another which considers time-varying internal influence. Interpersonal communication among firms is revealed as the determinant factor in the diffusion process of franchising.

The diffusion process of frequently purchased consumer products, such as prescriptions drugs, is modeled as a process of trial and repeat. The incorporation of marketing instruments in the diffusion model improves the understanding of the diffusion process of prescription drugs. Managers can improve the trial rate of their new drugs by investing in own marketing instruments, but the trial rate decreases with competitors' marketing expenditures.

We show that pharmaceutical marketing has both an informative and persuasive influence on the diffusion of new prescription drugs. Specifically, the “informative” function of pharma marketing influences the diffusion of new drugs through trial rate and the “persuasive” function through repeat rate. The differentiation between direct-to-physician marketing (“push” strategy) and direct-to-consumer advertising (“pull” strategy) is a relevant factor to be considered for managers. Direct-to-physician marketing clearly affects the trial and repeat rates whereas direct-to-consumer advertising seems to affect the trial rate through internal influence during the first year and the repeat rate during the complete period. However, direct-to-consumer advertising has no demonstrable impact on the trial or repeat rates when the drug categories include both branded and generic drugs. Furthermore, in the particular case in which the category has only branded drugs, earlier entrance in the market creates barriers of entry. Finally, the pharmaceutical companies can increase the propensity to try new brands and also the repeat rate from the first year after introduction by intensifying their marketing activities. This allows these companies to favor the trial of new drugs and to protect themselves from competitors’ products from the first year after introduction.

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Nederlandse samenvatting

Het modelleren van diffusiepatronen van innovaties

Het concurrentieklimaat, nieuwe mogelijkheden dankzij technologische ontwikkelingen en de veranderende vraag van afnemers leiden ertoe dat bedrijven producten verbeteren en vernieuwen. Deze nieuwe producten moeten worden ontwikkeld, getest en met succes op de markt worden gebracht. Dit is één van de hoofdtaken van het management. Gezien de complexiteit, de risico's en de hoogst dynamische aard van deze taak hebben managers de juiste middelen nodig om hun werk naar behoren te doen. Diffusiemodellen verstrekken belangrijke informatie om de dynamiek van het op de markt introduceren van nieuwe producten te doorgronden.

In diffusiemodellen wordt de verspreiding /diffusie van een nieuw product in de tijd beschreven. Producten worden geadopteerd door klanten. De mate waarin en de snelheid waarmee dit gebeurt bepaalt het (commerciële) succes van een nieuw product. Tevens bepaalt dit de vorm van de curve die de levenscyclus van het product representeert. De diffusie van een nieuw product wordt bepaald door externe factoren (reclame, mate van distributie, prijs) en interne factoren. Bij de interne factoren gaat het om de onderlinge beïnvloeding van de gebruikers. Mond-tot-mond-reclame speelt daarin de belangrijkste rol. Welke ervaringen hebben afnemers met het nieuwe product en hoe zijn deze ervaringen? Dit proces kan trouwens door externe factoren gestimuleerd worden. In (bijna) alle diffusiemodellen spelen externe en interne factoren een rol. Tevens houdt men rekening met de omvang van de (potentiële) markt en met de mate waarin op een bepaald tijdstip een nieuw product door de markt geaccepteerd is. Het werk van Bass (1969) is de aanzet geweest tot het gebruik van diffusiemodellen in de marketingpraktijk en in de marketingwetenschap in de afgelopen drie decennia.

Met dit proefschrift willen we een bijdrage leveren aan de methodologische en substantiële ontwikkeling van diffusiemodellen en enkele nieuwe toepassingen geven.

In hoofdstuk 1 behandelen we het belang van inzicht in het diffusieproces voor innovaties en hoe diffusiemodellen hierbij een rol spelen. In de volgende hoofdstukken presenteren we theoretisch en empirisch onderzoek naar diffusiemodellen. Door middel van een analyse van actueel onderzoek en enige voorstellen tot het ordenen van diffusieprocessen van nieuwe goederen en diensten dragen we bij aan de kennis van diffusiemodellen.

In hoofdstuk 2 kijken we terug op de theoretische en empirische achtergronden van diffusiemodellen in marketing. We evalueren deze modellen en bespreken de beperkingen van bestaande diffusiemodellen. Diffusiemodellen zijn gebaseerd op diverse veronderstellingen. De volgende worden frequent gehanteerd:

1. tijdens het diffusieproces, wat een binair proces is (wel of niet aanschaffen van een nieuw product) blijft de populatie homogeen;
2. gedurende het diffusieproces blijft de grootte van de populatie gelijk;
3. gedurende het diffusieproces blijven de interne en externe diffusieparameters gelijk;
4. tijdens het diffusieproces is slechts één adoptie per klant toegestaan;
5. het diffusieproces speelt zich af binnen geografische grenzen;
6. de diffusie van het nieuwe product wordt onafhankelijk van de ontwikkeling van producten van de eigen en concurrerende organisaties beschouwd;
7. gedurende het diffusieproces blijven de kenmerken van het nieuwe product constant;
8. gedurende het diffusieproces is er geen restrictie op het aanbod van het nieuwe product;
9. gedurende het diffusieproces wordt de invloed van marketingvariabelen impliciet meegenomen door de parameters van het model.

De klassieke of traditionele diffusiemodellen zijn gebaseerd op alle hierboven genoemde veronderstellingen en missen daardoor belangrijke details. Hoofdstuk 2 laat zien hoe deze modellen kunnen worden aangevuld met andere elementen. De nieuwe modellen die wij ontwikkelen betekenen een belangrijke verbetering in het doorgronden van structuren en krachten die diffusieprocessen van nieuwe producten sturen.

In de volgende hoofdstukken bespreken we specifieke uitbreidingen van de klassieke diffusiemodellen en passen deze toe in diverse contexten. In hoofdstuk 3 leiden we de empirische toepassingen in. Deze hebben betrekking op de distributie van films in Spanje, Frankrijk en Italië (hoofdstuk 4), de introductie van franchising in Spanje (hoofdstuk 5) en de diffusie van medicijnen in de USA (hoofdstuk 6).

In hoofdstuk 4 ontwikkelen we een zogenaamd ‘generalized Bass-model’ waarin de variabele distributie expliciet wordt meegenomen. Zo wordt de invloed bepaald van distributie op het diffusieproces van, in dit geval, nieuwe films. De films worden geïntroduceerd in drie landen: Spanje, Frankrijk en Italië. We gaan na of de diffusieprocessen van dezelfde producten al dan niet verschillend zijn tussen de landen ('country effect'). Tevens is onderzocht of de tijd tussen de introductie van dezelfde film in twee landen van invloed is op het diffusieproces in het derde land. Daarbij is het derde land het land waar de film als laatste wordt geïntroduceerd ('time effect').

Met behulp van weekgegevens die betrekking hebben op 21 films en de periode september 1997 t/m februari 1999 zijn diverse diffusiemodellen geschat. Alhoewel het aantal bioscopen waar een film vertoond werd (distributie) enige invloed had op het diffusieproces hebben (1) externe factoren (reclame, filmkritieken) en (2) mond-tot-mond reclame doorgaans vaker een significant effect op de mate van adoptie van een nieuwe film dan de distributiegraad.

Bovendien hebben we *country effecten* gevonden. Er bestaan significante verschillen in voorkeuren tussen Spanje en Frankrijk en tussen Italië en Frankrijk, maar niet tussen Spanje en Italië. De culturele, economische, sociale of andere verschillen tussen Spanje en Italië schijnen niet zo groot te zijn dat deze significante verschillen in diffusieprocessen van films opleveren. Het *time effect* blijkt evenwel van minder belang. Of men de films min of meer tegelijk introduceert of de introductie in de tijd tussen de verschillende landen spreidt heeft geen of weinig effect op het diffusieproces.

In hoofdstuk 4 worden drie van de negen beperkingen van het Bass-model afgezwakt. Het betreft hier de veronderstellingen 2, 3 en 9. Ten eerste mag de potentiële markt dynamisch zijn; in ons model staan we toe dat distributie de potentiële markt vergroot (aanname 2). Ten tweede staan we toe dat de parameters van interne en externe invloed variëren tijdens het diffusieproces van de innovatie; oftewel: we nemen aan dat distributie van invloed is op de acceptatiegraad van een nieuw product (aanname 3). En ten derde nemen we de invloed van een marketing variabele (distributie) expliciet in beschouwing (aanname 9).

Hoofdstuk 5 richt zich op de toepassing van nieuwe diffusiemodellen bij organisatorische vernieuwingen. Hier is tot nu toe weinig onderzoek naar gedaan. Deze studie wil deze leemte opvullen door een organisatorische vernieuwing, franchising, onder de loep te nemen. Er bestaan geen voorgaande onderzoeken die de verspreiding van franchising vanuit de invalshoek van de franchisenemer bekijken. Nevers (1972) bestudeerde hoe een franchiseketen nieuwe franchisenemers opneemt in zijn bedrijf; *intra-firm diffusion*. Wij onderzoeken hoe franchising, beschouwd als een vorm van bedrijfsorganisatie, in Spanje wordt toegepast; *inter-firm diffusion*. We bekijken hoe de franchiseformule in Spanje wordt uitgewerkt gedurende de periode 1974-1999. We passen bekende diffusiemodellen toe om te zien hoeveel bedrijven zijn beïnvloed door tot franchising overgegane bedrijven ("*imitators*") en hoeveel bedrijven hier niet door zijn beïnvloed ("*innovators*"). We ontwikkelen een vierstaps benadering om het meest adequate model te bepalen. Na een visuele analyse van de gegevens testen we of de overgang naar franchising een toevallige beslissing is of dat dit voortkomt uit imitatie van andere bedrijven. In de tweede stap her-examineren we deze imitatie-hypothese in navolging van Mahajan, Sharma en Bettis (1988). In de derde stap vergelijken we de uitkomsten van diverse modellen met elkaar. Dit doen we in twee stappen. Allereerst worden de geneste modellen met elkaar vergeleken en worden op basis van statistische criteria keuzes gemaakt (stap 3). Ten slotte worden de modellen die niet genest zijn met elkaar vergeleken met behulp van predictieve validatiecriteria.

Onze resultaten bevestigen de toepasbaarheid van de imitatie-hypothese bij franchising. Van de acht gepresenteerde diffusiemodellen (met zowel een vaste als een dynamische potentiële markt) blijven na stap 3 drie modellen over die het meest geschikt zijn om het diffusieproces van het franchiseconcept bij Spaanse bedrijven te beschrijven. Het klassieke Bass-model blijkt van deze drie modellen de beste predicties op te leveren. De resultaten van dit model laten zien dat de overgang naar franchising significant maar licht wordt beïnvloed door externe invloeden. Dit veronderstelt dat wanneer de Spaanse overheid Spaanse franchiseorganisaties of Spaanse franchisebeurzen wil stimuleren om over te gaan tot franchising, marketinginspanningen daarbij een rol kunnen spelen. De interne, onderlinge beïnvloeding van bedrijven is evenwel veel groter.

We merken op dat bij deze organisatorische vernieuwing –franchising- de besluitvormer niet de consument is maar het bedrijf. In dit hoofdstuk stellen we de eerste drie veronderstellingen van het Bass-model bij. We houden rekening met (1) een heterogene populatie, (2) een populatie die in de tijd verandert en (3) een variërende parameter voor de interne invloed op het diffusieproces.

In hoofdstuk 6 ontwikkelen we diffusiemodellen om de effecten van marketinginspanningen op de diffusieprocessen van geneesmiddelen te bepalen. We ontwikkelen een model dat gebaseerd is op een model van Hahn et al. (1994) om deze effecten te bepalen op de 'probeeraankopen' ('trial') en 'herhalingsaankopen' ('repeat purchases') van geneesmiddelen in de categorieën rhinitis, osteoarthritis-reumatoïde-arthritis en asthma. Daarnaast wordt nagegaan of marketinguitgaven een effect hebben op de mond-tot-mond-beïnvloeding ('internal influence'). De (maandelijkse) gegevens hebben betrekking op de Verenigde Staten en op de periode 1993-2000. We maken een onderscheid in de effecten van marketinginspanningen die gericht zijn op degenen die geneesmiddelen voorschrijven (doctoren) en finale afnemers, d.w.z. patiënten. In de Verenigde Staten bestaat de mogelijkheid om reclame te maken voor geneesmiddelen gericht op finale afnemers. Wanneer men dit doet kiest men voor een 'pull'-strategie. De activiteiten die gericht zijn op het beïnvloeden van doctoren maken onderdeel uit van een 'push'-strategie.

Het bepalen van de effecten van marktinstrumenten op de 'trial rate', de 'repeat purchase rate' en op de interne beïnvloeding (van artsen en van patiënten) vindt in twee stappen plaats. Eerst schatten we varianten van de door Hahn et al. ontwikkelde diffusiemodellen voor de relevante merken in een categorie. Vervolgens relateren we de geschatte 'trial rate', 'purchase rate' en de parameter die de 'internal influence' representeert aan de marketinguitgaven in een cross-sectionele analyse. Tevens wordt de entreevolgorde van een geneesmiddel op een markt als verklarende variabele gebruikt.

Met behulp van deze analyses kunnen we aantonen dat de marketing van geneesmiddelen een informatieve en een overredende functie heeft. Marketinguitgaven beïnvloeden zowel de 'trial rate' (informatieve functie) als de 'repeat rate' (overredende functie). Daarbij hebben de activiteiten die in het kader van een 'push'strategie ingezet worden significante effecten op de 'trial' en 'repeat' rate. De direct-op-de-finale klant gerichte reclame is van invloed op de 'trial rate' in het eerste jaar dat een medicijn op de markt is. De 'repeat rate'wordt gedurende de gehele periode positief beïnvloed door DTC (direct to consumer)-reclame.

De cross-sectionele analyse geeft tevens inzicht in de volgorde van het op de markt komen van een nieuw medicijn en de betekenis van merk- versus generieke medicijnen. De volgorde van het op de markt komen blijkt een belangrijke rol te spelen in de lanceerstrategie van nieuwe producten in de rhinitis-categorie. Vroeg op de markt gebrachte medicijnen hebben een betere kans op een bevoorrechte positie op de medicijnenmarkt. Echter als we de andere categorieën beschouwen blijkt de volgorde van binnenkomst minder belangrijk te worden. Deze categorieën bevatten ook andere dan merkmedicijnen, te weten 'generieke' producten.

In dit onderzoek worden vier veronderstellingen van het Bass-model aangepast. We veronderstellen dat marketingvariabelen het diffusieproces intern en extern beïnvloeden (aanpassing van veronderstelling 3). Vervolgaankopen worden expliciet in het diffusiemodel opgenomen (aanpassing van de vierde veronderstelling). Tevens houden we rekening met de mogelijke effecten van concurrenten (veronderstelling 6) en we nemen expliciet de effecten van marktinstrumenten in beschouwing (aanname 9). De invloeden van marketingactiviteiten zoals artsenbezoeken, advertenties in vakbladen, medische bijeenkomsten en DTC-reclame nemen we expliciet mee in het onderzoek.

In hoofdstuk 7 presenteren we de conclusies en bijdrage van dit proefschrift en bespreken we de beperkingen alsmede de richting voor verder onderzoek.